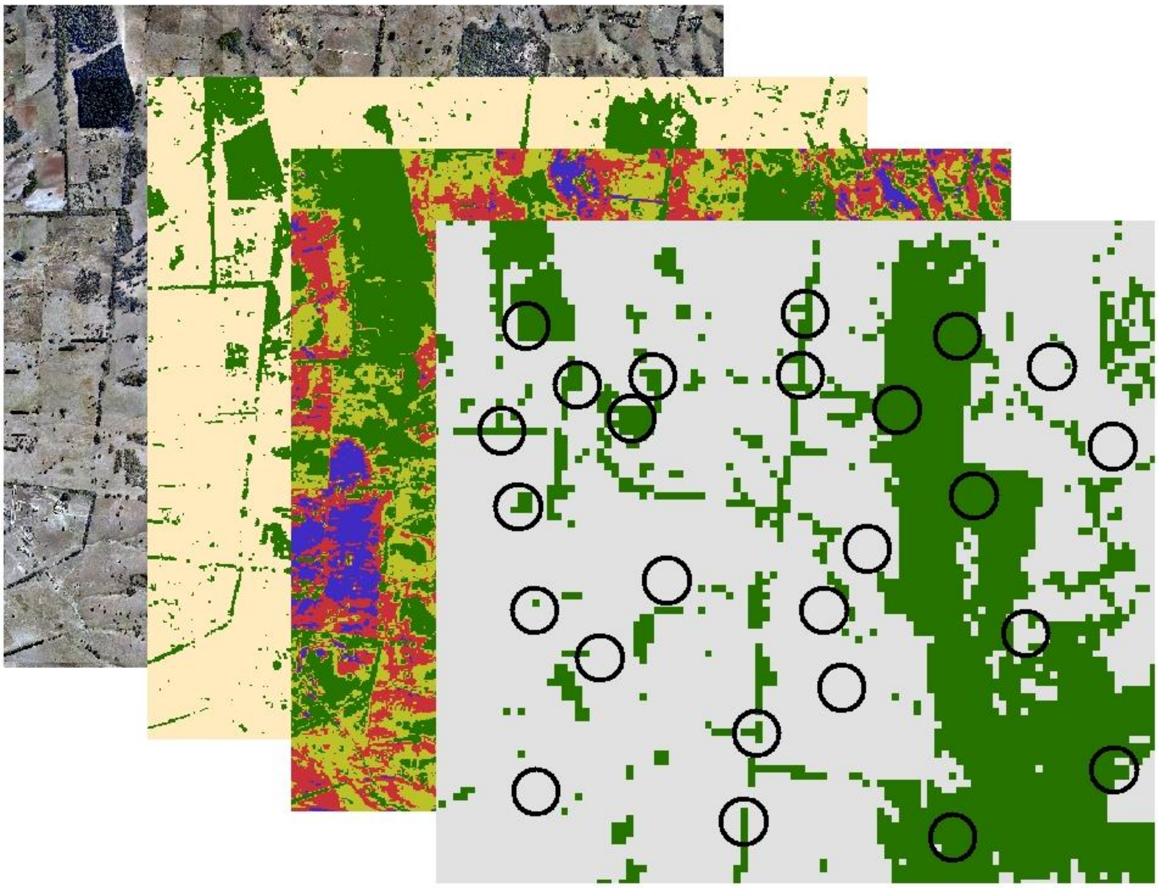
Scale in remote sensing and its impact on landscape ecology



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A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy.

Author’s declaration

I hereby declare that except where due acknowledgement has been made, the work is my own, the work has not been submitted previously, in whole or in part, to qualify for any other academic award and the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program.

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Abstract

The use of remotely sensed derived thematic data has become ubiquitous in landscape ecology. Remote sensing data has the potential to describe broad scale landscape patterns and relate them to ecological processes such as species persistence and distribution. However, these datasets are being used in ecological analyses without considering the spatial uncertainty that is ever present in remote sensing data. Maps derived from remote sensing data will vary in the extent, patchiness and accuracy of their land cover classes, predominantly due to a number of scale dependent factors such as pixel size, minimum mappable unit and extent and their interactions. Furthermore, the effect of these factors on land cover classification is more pronounced in spatially complex fragmented environments, which are often the subject of landscape ecological studies.

This thesis investigated the interaction and the relative importance of scale dependent factors on the characterisation of landscape pattern and ecological analysis using real and synthetic land cover data and simulated species-environment models. The research in this thesis is divided into four parts: 1) a systematic review of the use of spatial data in landscape ecology and how spatial uncertainty is currently addressed; 2) effects of scale on the classification and extraction of small and linear patches; 3) the effects of scale on the characterisation of landscape pattern; and 4) the effects scale on deriving species-environment relationships.

Part 1 of the thesis is a systematic review of the literature investigating the degree to which landscape ecologists use spatial data and how they deal with spatial uncertainty when conducting spatial analyses. In the first part of this chapter a general literature search was carried out and a set of five scale dependent factors that have a demonstrated effect on the characterisation of landscape pattern and ecological analyses were identified. These factors were pixel size, minimum mappable unit, smoothing, thematic resolution and extent. Along with scale dependent factors, classification error was also identified as having an effect. The second part of the chapter systematically reviewed all articles published in the journal *Landscape ecology* in 2007 and recorded how spatial data was used and whether scale dependent factors and classification error were addressed or reported in ecological analyses. The systematic review found that these factors were rarely addressed and reported. Furthermore, of the studies which investigated the effects of the scale dependent factors very few investigated the effects of more than one of these factors. The review found that studies nearly always used the default pixel size of the sensor which in most cases was either the

~30m pixel size of the Landsat satellite (used in 46% of the studies reviewed) or ~1m pixel size of aerial photography (used in 53% of the studies).

Part 2 of the thesis investigated the impact of scale on the classification and extraction of single patches. It specifically looked at ecologically important small and linear vegetation patches using a simulation model. This study found that mapping error was highest when the scale of the feature and the raster grid coincided. Ecologically important landscape elements such as small and linear vegetation patches of similar scales to the raster grid had lower classification accuracies, and were less likely to be extracted than larger more compact features. The simulation model demonstrated that the spatial resolution of the grid should be many times finer in order to extract small and linear features accurately.

Part 3 of the thesis looked at the effects of scale on the characterisation of landscape pattern. While the second chapter investigated the classification of single patches this chapter looked at how whole landscapes are affected by scale. The effects of scale dependent factors (pixel size, smoothing and extent) on landscape pattern were tested on a binary presence/absence tree cover maps of Victoria. Landscape pattern was measured using landscape metrics and class area. This study found that at coarser scales, subtle levels of patchiness declined. Small patches either aggregated into larger patches or completely disappeared. However, estimates of total class area remained constant regardless of scale. While the effects of scale dependent factors on some components of landscape pattern were predictable, this was not always the case (for example, the effect of changing pixel size or applying a smoothing filter was not consistent). This study showed that scale dependent factors interact and may need to be considered simultaneously in order to assess the effect of scale on the characterisation of landscape pattern.

The final part of the thesis investigated the effect of scale of the remote sensing data on the identification of the scale at which a species interacts with the environment. This was done using a simulated multi-scale species-environment model. The species-environment model used a common multi-scale experimental design that compares the relationship between ecological attributes (e.g. species diversity) calculated with point data and environmental data (e.g. vegetation cover) for the surrounding area within buffers of multiple sizes. The environmental data was represented with synthetic and real landscapes. The common practice in studies of this kind is to identify the scale of operation as the scale (buffer size) at which the highest correlation between environmental and ecological variables occur. In these studies the analysis unit is multi-scale, however the land cover data used to measure the environmental variable is usually represented by a single scale, typically the pixel size of the remote sensing image. This study found that varying the scale of the environmental data by changing pixel size and/or applying a smoothing filter affected the scale of operation identified. Thus, in some cases the results of a study identifying the scale of operation will be flawed when the scale of the remote sensing data is incorrect. This is what is known in the literature as the modifiable areal unit problem (MAUP).

In conclusion, this thesis quantified the impact of scale on the classification of land cover maps and demonstrated how spatial uncertainty in the characterisation of landscape pattern can impact on ecological analyses. Without the incorporation of uncertainty arising from scale, ecological analyses using remote sensing data will continue to produce results with unquantified uncertainties, which may result in poor and/or ineffective management decisions.

Preface

The work presented herein was completed as a body of work for this thesis and is substantially my own work. Publications and contributions from others are detailed below:

The content in Chapter 2 is based on a paper in preparation:
Lechner, A. M., S.A. Bekessy, S. D. Jones, S, and W.T. Langford (preparation) Scale and error in remote sensing: Are landscape ecologists addressing these issues?

The work presented in Chapter 3 was published as:
Lechner, A.M., A. Stein, S.D. Jones, and J.G. Ferwerda (2009) Remote Sensing of small and linear features: Quantifying the effects of patch size and length, grid position and detectability on land cover mapping. Remote Sensing of Environment 113: 2194-2204

The work presented in Chapter 4 was published as:
Lechner, A.M., S.D. Jones, and S. A. Bekessy (2008) A study on the impact of Scale Dependent Factors on the Classification of Landcover maps in A. Stein, J. Shi, and B. Wietske, editors. Quality Aspects in Spatial Data Mining (pp. 315-328): Chapman and Hall/CRC Press.

Lechner, A. M., S. D. Jones, and S. A. Bekessy (2007) Development of a framework to assess the impact of Scale dependent factors on the classification of landcover maps. Proceedings of the 5th International symposium on Spatial Data Quality ISSDQ 2007, Modelling qualities in space. ITC, Enschede, Netherlands.

The content in Chapter 5 is based on a paper in preparation:
Lechner, A. M., W.T. Langford, S. D. Jones, S. A. Bekessy and A. Gordon, (preparation) Investigating pattern processes relationships at multiple scales: differentiating between scale of operation and scale of observation.

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I would like to thank Jelle Ferwerda who provided help and advice during the beginning of my PhD and was an instigator in getting me to learn IDL. Thanks to Karin Reinke who has always been very enthusiastic about my work and provided great feedback and encouragement.

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Finally, thanks to my family and friends who always supported me throughout this ordeal. Thanks to Kat (Marcoux) who composed the title of my thesis while her head was cut open and bleeding in a hospital waiting room…that's dedication. And finally special thanks for all the help provided by my partner Nickyy, who has only known me as a stressed out PhD student. I hope that wasn't what attracted you to me.

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Chapter 1 Introduction

1.1 Introduction

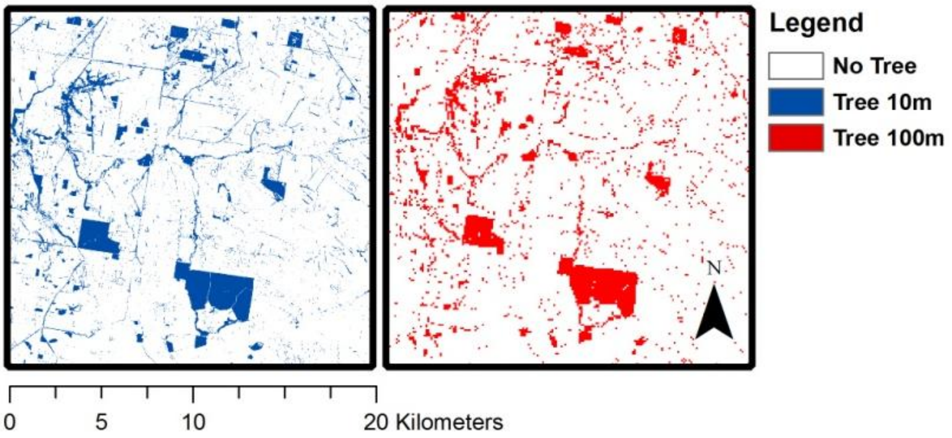
Understanding earth system processes and monitoring human interactions within them is becoming increasingly important (Vitousek et al. 1997; Wu and Hobbs 2002). This understanding is vital to meet the needs of decision makers for quantitative data regarding the negative consequences of environmental change, and the opportunity for responding to those changes (Hassan et al. 2005). The difficulty of this task is compounded by the large scale at which these processes occur such as climate change, deforestation, desertification, reductions in biological diversity, impacts of vegetation fragmentation and pollution. Gathering a total sample of environmental and ecological data at these global and landscape scales[1] is only practical through the use of satellite earth observation and is now both widespread and mandated at national and international levels (e.g. Convention on biodiversity (2007), Kyoto protocol (United Nations Framework Convention on Climate Change 1997) and European Community biodiversity strategy (European Community 1998)).

In landscape ecology, remote sensing from satellite and aerial platforms is used to estimate the type and extent of land cover across natural and human dominated landscapes and relate these to ecological processes. Remote sensing addresses a fundamental need of landscape ecologists to describe physiographical characteristics of the earth's surface ranging from bare rock to forests at the landscape scale. Traditional field ecological data do not provide the timely, broad scale and cost effective environmental data that is necessary to answer many ecological questions (Gergel 2007; Kerr and Ostrovsky 2003; Nagendra 2001). Thus, the use of remote sensing derived land cover maps in landscape ecology has become ubiquitous. Land cover maps are used for the identification of vegetation types and derivation of habitats for ecological analyses such as the derivation of landscape metrics (Griffith et al. 2000), change detection analysis (Kennedy et al. press), habitat suitability/prediction (Guisan and Zimmermann 2000; Leyequien et al. 2007), population viability analysis (Southwell et al. 2008), and conservation planning (Margules and Pressey 2000).

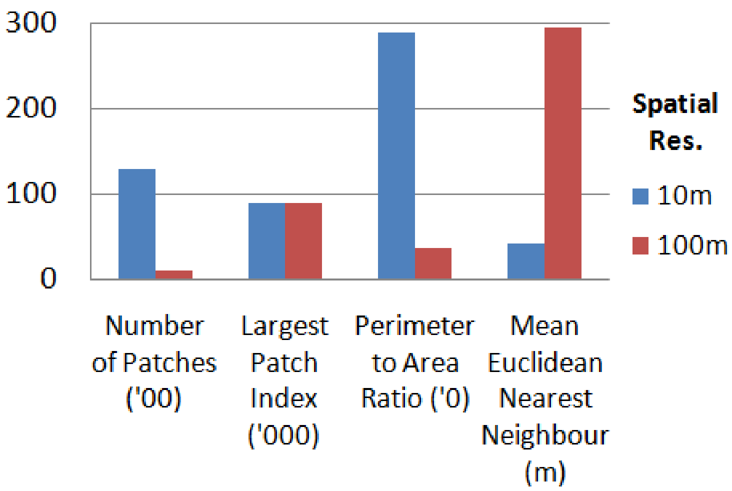
One of the main focuses of research in landscape ecology is understanding the relationship between landscape pattern[2] and landscape processes (Pickett and Cadenasso 1995; Turner

[1] *Landscapes* can be considered large spatially heterogeneous geographic areas containing a diverse number of natural and modified ecosystems at the scale of kilometres (Forman and Godron 1986) or an abstraction or representation of representing an ecological system describing spatial heterogeneity at any scale (Lidicker Jr 2008, Turner et al. 2001)
[2] *Landscape pattern* refers to the structure, location and composition of landscape elements or landcover such as vegetation remnants.

1989). The characterisation of landscape pattern, however, it is affected by spatial uncertainty which has the potential to negatively affect analyses. Spatial uncertainty arises from many sources; the most recognised being scale dependent factors such as pixel size (e.g. Wu et al. 1997) and the thematic resolution (e.g. Buyantuyev and Wu 2007). The scale of remote sensing data will affect both the structure and composition of landscape elements. Consequently the interpretation of certain ecological functions of a landscape will change depending on the scale at which the map is created (Figure 1.1), as patterns measured at one scale may not hold at other scales (Schneider 2001).



a)



b)

Figure 1.1 Tree presence/absence classification at two different pixel sizes: 10m and 100m (a). Small and linear vegetation patches and fine scaled fragmentation are absent in the low spatial resolution image (100m). Landscape metrics calculated for each image (b). Landscape metrics are often used in landscape ecology to quantify spatial pattern and link to ecological processes. All metrics except for the largest patch index are affected by scale. Thus, as landscape metrics can change with scale the interpretation of the ecological function of a landscape will differ with scale.

An understanding of the pattern-process relationship is confounded by the effects of scale on the representation of landscape pattern and the outcome of analyses is often scale dependent. For example, a common aim of analyses in landscape ecology is understanding the effect of landscape connectivity on species persistence (Turner 2005). However, the scale of commonly used remote sensing data such as Landsat 7 ETM+ with 30 metre spatial resolution is too coarse to adequately represent landscapes for this purpose, particularly for small or medium sized fauna. Patches such as small remnants and linear roadside vegetation which can be important for connectivity between different parts of the landscape may be classified inaccurately, and in some cases will not be identified at all. Thus, hypotheses regarding the importance of connectivity may be incorrectly rejected due to the coarse scale of the spatial data used. Conversely, high resolution data may extract small patches of vegetation that may be too small to be considered as habitat or as a wildlife corridor and thus the resulting map may represent a landscape with a high degree of connectivity that in reality does not exist for a particular species. While it is commonly assumed that it is preferable to use data with the highest spatial resolution, it is more appropriate for the spatial resolution of data to be determined by the scale at which a phenomenon operates (Turner 2005).

Users of remote sensing data rarely test for the effects of spatial uncertainty originating from scale, on analyses in landscape ecology. Remote sensing data users often utilise readily available generic data sets or create their own using remote sensing data at scales determined by the availability of sensors (Comber 2008; Meentemeyer 1989). Remote sensing maps are usually considered to portray the absolute truth (Evans 1997). The misuse of remote sensing data is partly the result of its widespread availability and the ease with which software can process the data (Fassnacht et al. 2006; Gergel 2007). Many users of remote sensing data do not have the time or ability to analyse the data themselves or understand the creation process (Adams and Gillespie 2006; Wiens et al. press). It is important for data users to understand the implications of using data that imperfectly models the phenomenon under investigation, as spatial uncertainty and error is always present in remote sensing data (Hess 1994; Kardos et al. 2006). The consequences of ignoring spatial uncertainties is that analyses and conclusions may be incorrect, leading to poor or ineffective management decisions (Jones et al. 2004; Lam et al. 2005).

Few studies have investigated the relationship between spatial uncertainty and the characterisation of spatial pattern using remote sensing data. Users rarely test the impact of scale and error on their analysis, yet in some cases this can have a profound effect (e.g.

Jelinski and Wu 1996; Wu 2004). To date there has been a lack of research that investigates the propagation of error from the initial creation of spatial data through to the end-use spatial analysis in fields that conduct spatially explicit analysis such as landscape ecology. It is unclear what effect these errors have on spatially explicit analyses as there have been few studies in this area due to the complexity of the relationship between input data and output error (Heuvelink 2002).

The research conducted in this thesis addresses the effects of scale on the characterisation of landscape pattern. It focuses specifically on the classification of ecologically relevant landscape entities and modelling processes used in landscape ecology. Few studies have considered how the numerous scale dependent factors interact with landscape heterogeneity. There is a lack of quantitative research investigating this issue, as most research in remote sensing tends to focus on a single landscape. This thesis uses quantitative landscape scale research with large sample sizes of real and synthetic landscapes to develop an understanding of the relationship between scale and spatial pattern characterisation error. The results of this research will assist users of spatial models to understand the effects of scale on their analyses.

1.2 Research objectives

The main objectives of this thesis are: 1) to develop a framework for assessing spatial uncertainty that is ecologically significant, and, 2) to investigate the interaction of scale dependent factors and classification accuracy on the characterisation of landscape pattern and the outcome of ecological analyses.

1.3 Research questions

The following key questions are addressed in this thesis:

1. Are landscape ecologists addressing spatial uncertainty when conducting analyses (Chapter 2)?
2. How do the scale dependent factors affect the characterisation of landscape pattern and how do they interact (Chapters 3, 4)?
3. How does scale in remote sensing data affect ecological analysis (Chapter 5)?
4. What are some potential ways forward for the disciplines of landscape ecology and remote sensing to deal with spatial uncertainty (Chapter 6)?

1.4 Thesis outline

This thesis is written so that each chapter, excluding the introduction and synthesis, can be read independently as standalone articles. These research chapters have all been accepted, submitted or are in preparation for peer-review publication. The chapters are the same as the published versions except the formatting has been changed to maintain a consistent style through the thesis and the references cited have been compiled into a single bibliography found at the end of the thesis. The thesis comprises 6 chapters, 4 of which are research chapters investigating different components of the theme outlined in the research objectives, whereby each chapter builds on the findings of the previous chapter.

Chapter 2 provides a systematic review of the literature to explore the degree to which spatial uncertainty is currently dealt with in landscape ecology. Furthermore, this chapter guides the research in subsequent chapters through identifying the factors that need to be tackled using experimental methods. The review identifies the current gaps in existing knowledge and provides a framework for investigating spatial uncertainty that is relevant to landscape ecology. Chapter 2 functions as a literature review for the entire thesis.

As the thesis progresses from chapter 3 to 5, the scale of enquiry expands. Chapter 3 investigates the classification of individual patches, while chapter 4 considers how landscapes composed of patches are affected by classification methods. The final research chapter 5 investigates how classification methods change the outcome of ecological analyses. These chapters all use the framework developed in chapter 2 for understanding the spatial uncertainty issues that are ecologically relevant.

Chapter 3 investigates the sources of spatial uncertainty that affect the extraction and classification of patches. This chapter focuses on small and linear patches which have ecological significance that is proportionally greater than their area. Computer simulation was used to analyse the relationship between scale of observation and the size of the patch and its affect on the outcome of classification. An understanding of classification at the patch scale is fundamental to understanding how spatial uncertainty affects the characterization of landscape pattern, where landscapes are composed of a number of patches of varying sizes and shapes.

Chapter 4 investigates ecologically relevant spatial uncertainty at the landscape scale using real regional scale remote sensing data in order to describe the impact of scale dependent factors on the characterisation of spatial pattern. This chapter specifically investigates the importance of testing more than a single scale dependent factor. Furthermore, the chapter functions as a pilot study to assess the appropriate sample size (as suggested by Dungan et al. (2002)) for the more complex simulation model developed in chapter 5.

The final research chapter 5 investigates the complete ecological analysis process, from representing the landscape using remote sensing data to ecological analysis that uses remote sensing data to describe landscape pattern. Chapter 5 brings together the understanding developed in chapter 3 and 4 regarding the effect of scale on the characterisation of landscape pattern and the associated error into a single simulation model using real and synthetic landscapes. It investigates the effect of scale of the remote sensing data on multi-scale species-environment models.

The final chapter 6 summarises the thesis findings and describes potential future directions for the disciplines of remote sensing and landscape ecology to deal with issues of spatial uncertainty.

Chapter 2 Scale and Error in Remote Sensing: Are landscape ecologists addressing these issues?

Planned publication:

Lechner, A. M., S.A. Bekessy, S. D. Jones, S, and W.T. Langford (in preparation) Scale and error in remote sensing: Are landscape ecologists addressing these issues?

2.1 Introduction

The use of thematic data derived from remote sensing is common in landscape ecology due to its wide availability, total sample, broad coverage and ecologically relevant spectral bands (Fassnacht et al. 2006; Gergel 2007; Hess 1994; Nagendra 2001; Reinke and Jones 2006). Remote sensing data processed using a geographic information system (GIS) is the most common form of data used to describe land cover in order to investigate the relationship between landscape pattern and ecological processes (Chen et al. 2008; Metzger 2008). However, due to its availability and the ease at which software can process remote sensing data it can be misused or used without an understanding of its limitations (Fassnacht et al. 2006; Gergel 2007). Maps that have been derived from remote sensing data are often treated to be the absolute truth (Adams and Gillespie 2006; Evans 1997), despite the uncertainty and error that is always present when simplifying and generalising the complexity of real world geographic phenomena (Kardos et al., 2006). The method used to classify remote sensing data will not only affect the map that is generated, but also the analyses and conclusions drawn from it (Wiens 2002). For example, depending on how habitat is classified, the interpretation of how a species responds to that habitat will also differ (Wiens 2002).

One of the main motivations of landscape ecology is to understand the relationship between landscape pattern and landscape processes (Knight and Landres 2002; Pickett and Cadenasso 1995; Turner 1989). The spatial pattern of habitat in a landscape affects the distribution and abundance of organisms (Turner 1989) as well as many other ecological processes, such as population persistence (Suter et al. 2007), species coexistence (Levin 1992) and species diversity (Griffiths et al. 2000). The relationship between pattern and process has been explored using a variety of empirical, deterministic and mechanistic models such as regression, metapopulation and habitat suitability models (Turner et al. 2001). These models, analyses and methods range from the derivation of landscape metrics (e.g. Debuse et al. 2007; Lechner et al. 2007), change detection analysis (e.g. Weiers et al.

2004), population viability analysis (e.g. Southwell et al. 2008), and conservation planning (e.g. Margules and Pressey 2000).

Two types of error confound the ability to use remote sensing data to investigate pattern-process relationships: (i) the often unknown *conceptual errors* associated with differences in the GIS/remote sensing geographic abstraction of a landscape and the true geographical representation as perceived by an ecological phenomenon (e.g. scale mismatch, incorrect variables measured); and (ii) the often known and measurable *representation errors* associated with producing or using remote sensing data that does not accurately represent the geographic abstraction of the ecological phenomenon (e.g. classification error) (Figure 2.1).

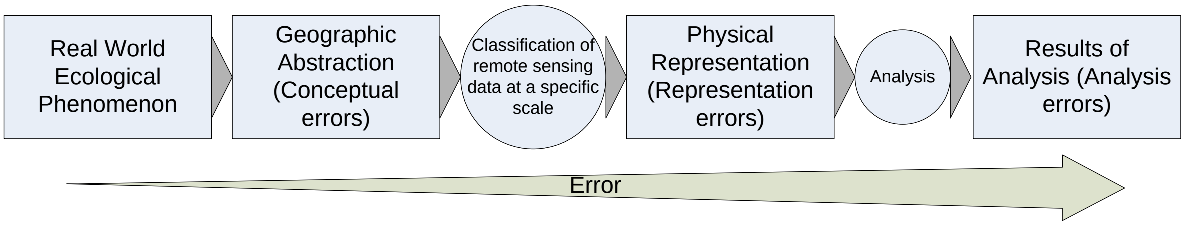


Figure 2.1 Schematic depiction of error propagation in landscape ecology, from the development of a geographic abstraction of the ecological phenomenon to analysis.

Accurate spatial analysis in landscape ecology is dependent on characterising landscape structure and composition at the appropriate scale without classification error. Scale mismatch will result in an ecological phenomenon remaining undetected (Levin 1992; Wiens 1989) or the results of an analysis will produce spurious relationships and erroneous conclusions might be derived (i.e. modifiable areal unit problem (MAUP))(Jelinski and Wu 1996; Openshaw 1984; Wu et al. 1997). In addition, classification error can propagate into analysis error which can further magnify that error (Hess 1994; Heuvelink et al. 1989; Langford et al. 2006)(see box 2.1 for further information on the MAUP). Figure 2.3 depicts some of the processes that are performed when creating a land cover map that can result in spatial error.

Box 2.1 The modifiable areal unit problem

The term modifiable areal unit problem (MAUP) is used to describe how analysis is affected by the arbitrary and modifiable size and shape of spatial units (Openshaw 1984). It is also known as the “zoning effect” in the social science community (Curran and Atikinson 1999). The MAUP is the result of the many ways in which non-overlapping units can be used to divide a study area for the purposes of analyses. It can be divided into two related components: the *scale* and the *aggregation* problem (Marceau and Hay 1999). The scale problem affects analyses as a result of changes in the spatial units through aggregated small units into progressively larger units or vice versa (Figure 2.2a-c). The aggregation problem affects analyses as a result of varying the boundary of areal units while keeping scale constant (Figure 2.2d-e). In remote sensing, the MAUP is a particular case where the units are controlled by pixel size, whereas in social sciences the size and shape of the areal units (i.e. census districts) are highly modifiable.

The MAUP has been demonstrated to affect both the classification accuracy of remote sensing images as well as ecological analyses using these remote sensing images. It not only affects the calculation of mean and standard deviation for the whole image but also the spatial distribution of high and low values within the image. In some cases the MAUP can render analyses meaningless (Dungan et al. 2002; Jelinski and Wu 1996; Nelson 2001; Openshaw 1984; Wu et al. 1997). For example, Fotheringham and Wong (1991) found that by modifying the spatial units nearly any correlation value could be obtained. Openshaw cautioned (Openshaw 1984) that the effects of MAUP must be addressed and must be treated as having an impact on analyses in the absence of evidence.

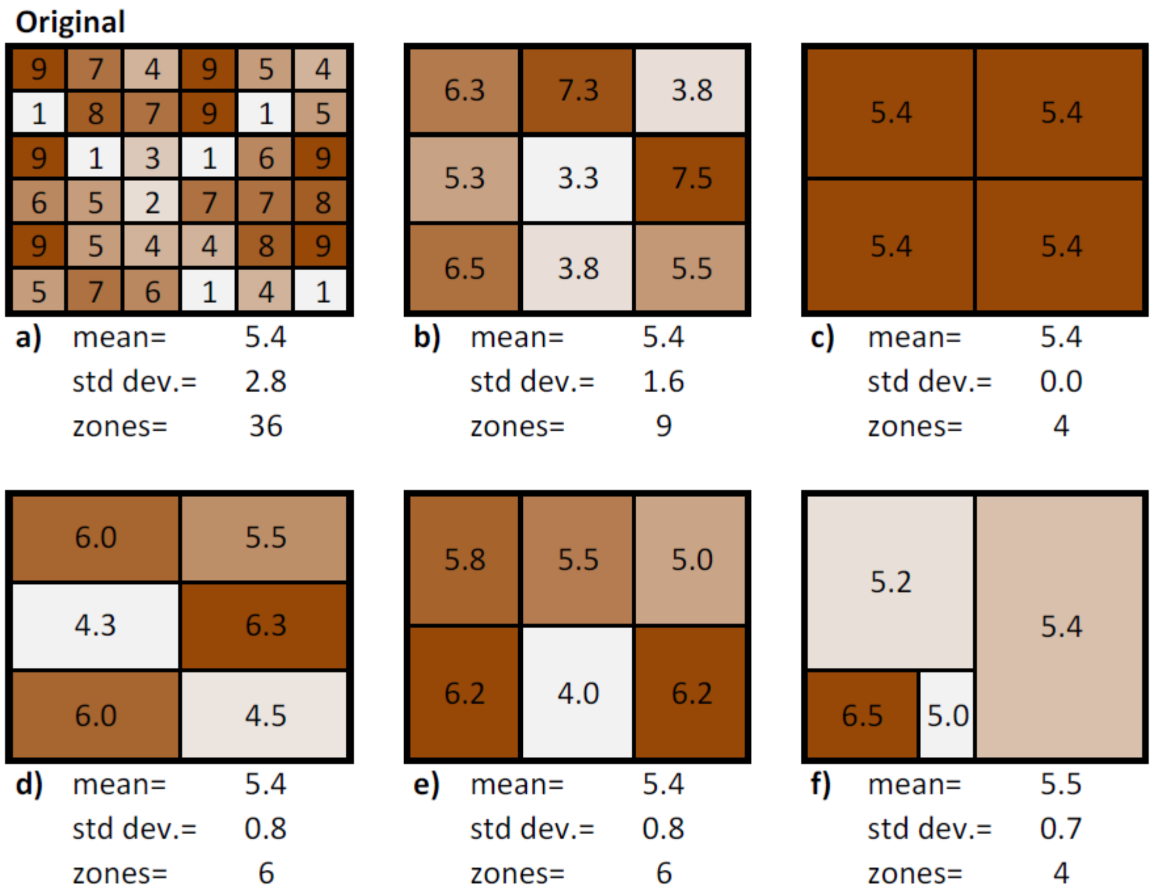


Figure 2.2 The effect of the MAUP. a) Original image. b-c) Original image aggregated to different pixel sizes (scale problem). d-e) Original image aggregated using zones with different shapes (aggregation problem). f) Original image aggregated using zones with different shapes at a different scale.

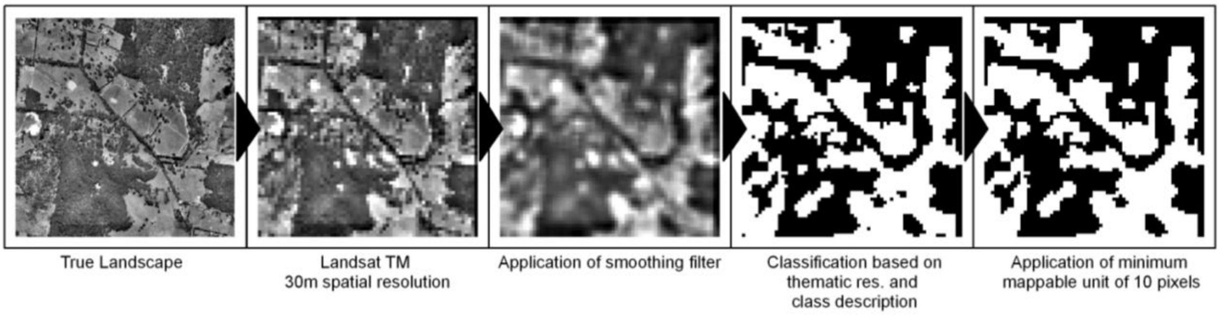


Figure 2.3 This figure depicts some of the processing that is performed when creating a land cover map that can result in spatial error. The accurate representation of landscapes is not only a property of the landscape itself but the method used to classify the landscape.

Despite the potential for spatial data uncertainty to have a profound effect on analyses, it is commonly ignored by ecologists (Hess 1994; Wiens 1989). For example, Rae (2007) tested the sensitivity of a graph based landscape connectivity model and found that recommended conservation networks varied by up to 101% due to uncertainty in spatial data. Similarly, Minor (2008) found that in a spatially explicit population model, spatial uncertainty in the input habitat map was the largest source of error, and was three times more important than uncertainty in other non-spatial model parameters.

This review investigates the degree to which landscape ecologists use spatial data and how they deal with spatial uncertainty when conducting analyses, specifically focusing on the effects of scale. It provides the background and justification for further research undertaken in the thesis.

I explore this by asking the following questions:

- How ubiquitous is remote sensing data in landscape ecology?
- What kinds of geographic representations are used in landscape ecology?
- Are landscape ecologists data users or data producers?
- Which components of landscape pattern (landscape composition and/or structure) are being addressed by research in landscape ecology?
- What kinds of spatial analysis are conducted in order to relate landscape pattern to ecological processes?
- Do landscape ecologists address and/or acknowledge scale issues?
- Do landscape ecologists address and/or acknowledge other forms of spatial uncertainty such as classification error?

Background information to each of these issues is provided and the implications for the discipline of landscape ecology are discussed.

2.2 Methods

An initial survey of the ecological literature was conducted in order to identify key remote sensing scale and classification error issues that influence the outcome of inference, prediction, and models that use spatial data. It focused on issues that affect the characterisation of landscape pattern using remote sensing data, such as *land use* and *land cover* datasets (LULC). For brevity, the scope was limited to spatial issues and temporal aspects were ignored; however, I acknowledge the importance of these issues in ecological studies (Bissonette and Storch 2003; Gustafson 1998).

As an analogue for the landscape ecology community, this study reviewed all the research articles published in the journal *Landscape Ecology* in 2007 (n=101). Review articles were excluded from the study. For each article, I recorded the degree to which landscape ecologists use spatial data and whether scale and classification issues were addressed and reported. This study only reviewed articles that used remote sensing data, which was considered to include aerial and satellite derived imagery. Simulated remote sensing data was not included as it is assumed that articles using simulated represent landscapes with 100% accuracy at the appropriate scale. In some cases, papers had to be excluded because the origin of the spatial data was not reported. This study did not make qualitative judgements as to whether they addressed the issues adequately, it only reported whether an attempt was made. Of the original 101 articles reviewed 15% of articles were not included due to inadequate information describing spatial data (n=15).

The results from the method of choosing papers may reflect a bias in *Landscape Ecology* to a particular subset of research in the field of landscape ecology. However, an alternative method using abstract search engines (e.g. Mayer and Cameron 2003; Wheatley and Johnson 2009) poses other issues because of the lack of clear definitions of ecological terms such as “landscape” and “scale” (Changyong and Lam 1997; Lepczyk et al. 2008; Mayer and Cameron 2003). An investigation of the *Scopus* abstract database searching for papers published in 2007 with the phrase “landscape ecology” in the title, abstract and keywords received 256 hits from 127 journals, mainly from ecological journals; however, the journals found ranged from *Health and Place* to *Cultural Geographies*. This indicates that many of these papers were not in the field of landscape ecology and thus a subjective decision about what exactly constitutes a landscape ecology paper would have to be made. Only 19 of the 124 articles published in *Landscape Ecology* in 2007 were found in this search, indicating high omission errors. Choosing to review papers only from *Landscape Ecology* ensured that this study did not include papers that are not about landscape ecology, where accurately describing spatial pattern is not important for these papers. However, there will be some bias caused by the omission of papers about landscape ecology published in other journals.

2.3 Results and Discussion

2.3.1 The origins and ubiquity of remote sensing data in landscape ecology

Remote sensing and GIS have been fundamental in the development of the landscape ecology discipline. The term *landscape ecology* was introduced in 1939 by Carl Troll, a German geographer who studied the interactions between the environment and vegetation using aerial imagery. Advances in remote sensing technology have allowed for the development of theoretical and empirical ecological studies that incorporate spatial heterogeneity at the landscape scale. Over the last thirty years, progress in sensor technologies, the greater availability of spatial data and powerful computers and software to manipulate this data have allowed for the widespread use of remote sensing in ecological studies (Chen 2008; Perry and Enright 2007; Wiens 1989). A significant turning point was the launch of the first Landsat satellite in 1972, which had a spatial resolution and a geographic coverage sufficient for landscape ecological research, making data more economical to use.

Today much of the geographic data used for landscape ecological research and land use planning is collected digitally as remote sensing or GIS data (Chen et al. 2008; Hilty et al. 2006). At the 2007 International Association of Landscape Ecology conference, Metzger (2008) reported that almost 60% of the abstracts presented had some kind spatial quantification or statistical analysis, using GIS, remote sensing, landscape indices or models. Mayer and Cameron (2003) reviewed landscape studies of terrestrial vertebrate ecology and found the majority of studies either used GIS or remote sensing data to describe habitat. This review found that 69% of articles in landscape ecology in 2007 that were not reviews or had inadequate information regarding the spatial data source used some kind of remote sensing data. Additionally, 15% used only GIS data and 16% used neither GIS nor remote sensing data (n=86) (Figure 2.4). Hereafter, the review only investigates the articles that contained remote sensing data (n=59).

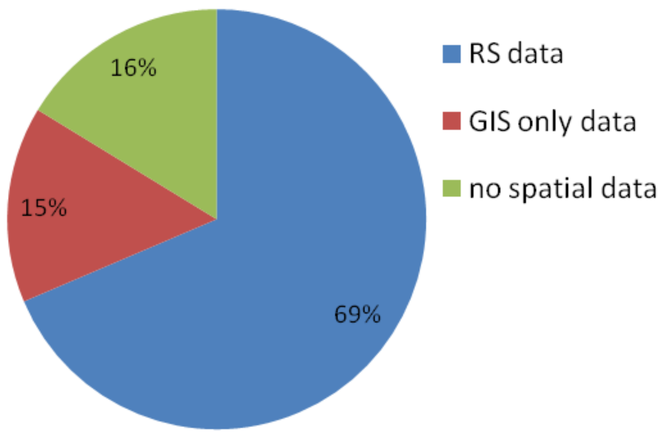


Figure 2.4 Proportion of articles that use remote sensing data (n=86).

2.3.2 Representing landscapes with remote sensing data

In landscape ecology the dominant geographic representation of landscapes are discrete *patches* of habitat surrounded by non-habitat (such as farmlands or urban areas), also known as the *matrix*. The *patch-matrix* perspective that classifies the landscapes into discrete objects was formalised by Forman and Godron (1986) and has become fundamental to landscape ecology (Antrop 2007). The principles of this model are founded in MacArthur and Wilson's (1967) island biogeography theory, which describes suitable versus unsuitable habitat (Gustafson 1998). Extensions of the *patch-matrix* model include the *landscape mosaic* model (Wiens 1995) and the *variegation* model (McIntyre and Barrett 1992). Both models consider the landscape to be composed of discrete areas with differing habitat conditions rather than the simple habitat versus non habitat representation used by the *patch-matrix* model. The *landscape mosaic* model considers the landscape to be composed of discrete patches of different types, varying in habitat quality. The *variegation* model is used to represent fragmentation at the landscape scale by considering the percentage of habitat loss for the total landscape. Further developments of the model by McIntyre and Hobbs (1999) considered differences in habitat conditions. Each of these models use the patch as a fundamental spatial unit; however, the physical meaning of patch varies greatly, depending on what is considered suitable by the ecological phenomena being studied and the scale at which it is observed.

Geographic representations of the landscape are derived from raw *raster* (sometimes referred to as fields, lattice, grid, or matrix) remote sensing images using automated statistical classification techniques. For higher spatial resolution, usual aerial imagery, classification is often done through manual aerial photo interpretation (API), whereby the landscape is represented as *vectors* (also known as entities, polygons or objects). At the analysis stage the classified data is often converted into discrete areal units using the patch-matrix or landscape mosaic model with ecological attributes such as vegetation type calculated as average values for each patch. Traditionally, patches are classified by differences in vegetation cover, soil, geology and human land use based on the requirements of the phenomena being researched (Wiens 2002). This study found that categorical/thematic classification schemes were the dominant models used to represent land cover in landscape ecology, with 25% of the articles reviewed using a binary classification scheme and 68% using a multi-class classification scheme (Figure 2.5).

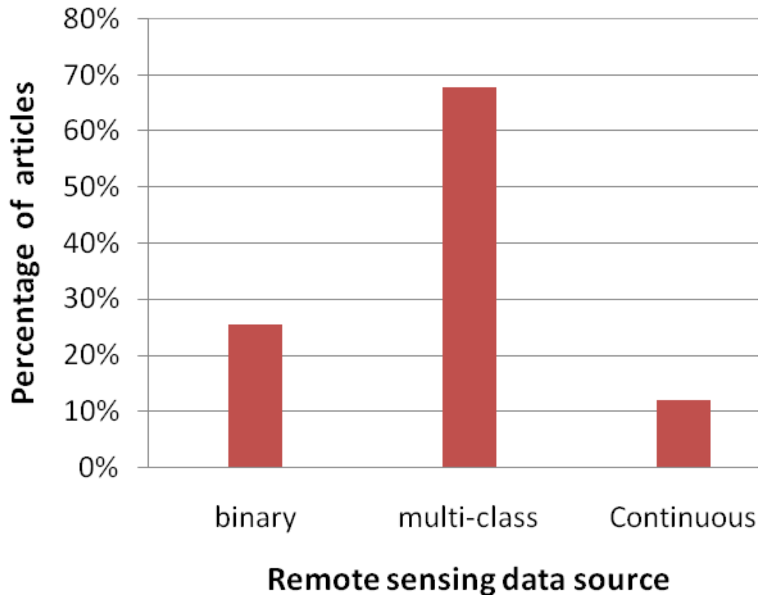


Figure 2.5 Remote sensing classification schemes used in the articles reviewed (n=59). Note, some studies used more than one remote sensing dataset.

Many alternative methods are available to represent landscapes, such as point based and continuous field data and fuzzy sets (Gustafson 1998; Robinson 2007). These alternative methods are rarely used, with continuous field data the only non-categorical classification scheme used. Approximately 12% of the remote sensing data used in the articles reviewed was continuous field data (Figure 2.5). Alternative classification methods are used in some cases because of the spatial uncertainty that arises from classifying complex natural objects into simple discrete classes. As landscapes are to some degree continuous (some more so than others) there are no definite boundaries between land cover classes and/or patches. Thus, there are an infinite number of ways in which to classify the landscape using a discrete classification system (Arnot et al. 2004; Burrough 1996; Schmit et al. 2006) and boundaries between classes can be subjective and artificial (Chapman et al. 2005; Powell et al. 2004). In some cases, continuous ecotones are discretised and give arbitrary labels such as vegetation community names that may not represent meaningful ecological differences ignoring spatial variability within patches (Gustafson 1998; Leyequien et al. 2007; Wiens 2002). Most ecological niche models assume that differences between classes are equal whereas in reality some classes are quite similar ecologically while others are very different (Chapman et al. 2005). Thus, the output of ecological models based on discrete classification systems will vary according to the classification scheme used. There are two key issues related to assigning land cover classes to geographic units that affect their use in landscape ecology: i) the use of *hard cover* classification schemes (i.e. one land cover class per pixel), used in both the patch-matrix and landscape mosaic models, which do not incorporate the range of sub-pixel variation, and ii) mismatches between the producer's and the user's conceptualisation of a map's land cover classes.

The first issue associated with using a hard cover classification scheme is that it will affect analyses such as the calculation of class areal extent (Foody 1996) and landscape metrics describing vegetation pattern (Arnot et al. 2004). An alternative to the hard cover classification commonly used to represent geographic phenomena is *soft/fuzzy* classification schemes, which have more than one value per pixel. The use of fuzzy classification schemes to represent spatial inputs into ecological modelling is unusual (Robinson 2007; Rocchini and Ricotta 2007); despite the increasing popularity of the approach by producers of remote sensing data. Fuzzy classification schemes in ecological models have mostly been used to map uncertainty in spatial outputs such as habitat models (e.g. Burgman et al. 2001; Regan et al. 2002).

The second issue associated with using a hard cover classification scheme is the ecological relevance of the classification scheme to the questions being asked. Maps will be classified based on the producers' objectives using different classification schemes with differing definitions of land cover classes (Burrough 2001; Colson et al. in press). The characterisation of landscape pattern depends on the system property being measured and the classification scheme used (Comber et al. 2005b; Congalton and Green 1993; Gustafson 1998; Li and Wu 2004). Therefore, classification can be subjective and unusable in different contexts. Even if the same class labels are used in maps produced by two different people, these classes will not necessarily be equivalent. A study by Cherill and McClean (1999) of vegetation surveying found that the average agreement between surveys conducted by six different field ecologists in the same month was only 25.6%, mainly due to differing interpretations of vegetation classes.

Variation in land cover schemes and class definitions may have as great an influence on the characterisation of a landscape as technical aspects, such as classification algorithm and pixel size (Comber et al. 2005b). The differences in classification scheme and class description will affect the outcome of spatial analyses using remote sensing data (e.g. Colson et al. in press; Cunningham 2006; Manton et al. 2005; Rae et al. 2007). A clear set of rules for defining classes is required for consistency (Congalton and Green 1999), however their specification is often not adequately described in metadata making the conceptualisation of land cover classes imprecise (Comber et al. 2005b). This is an important consideration when using readily available datasets, which are popular due to their availability and their low cost in comparison to developing new project specific maps (Comber et al. 2005a). Approximately

36% of articles reported using generic LULC datasets, such as Europe's CORINE dataset or the US's national land cover dataset (NLCD) (Figure 2.6). Furthermore, around 33% of articles using generic datasets aggregated LULC datasets to reduce the number of land cover classes often to create binary land cover map. Approximately 17% of all articles aggregated multi-class data to a smaller number of classes. The aggregation of land cover classes introduces further uncertainty as the rules for aggregating classes can be somewhat arbitrary (Quaife et al. 2008).

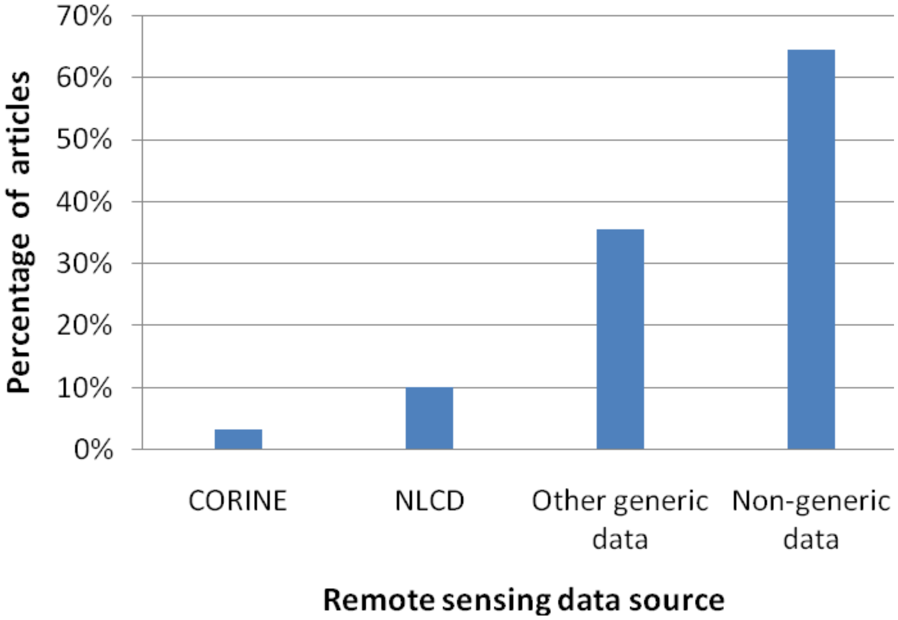


Figure 2.6 Sources of remote sensing land cover maps used in the articles reviewed (n=59). Non-generic data refers to maps generated specifically for the study, while generic refers to the use of generic land cover datasets that have been developed and made available for general use and have not specifically been generated for the ecological study. Note, some studies used more than one remote sensing dataset.

2.3.3 Landscape pattern

One of the central themes in landscape ecology is its focus on landscape heterogeneity (Wiens et al. 2007). In this study I use the term *landscape pattern* to describe spatial aspects of heterogeneity (i.e. the landscape mosaic), not including temporal aspects. Landscape pattern can be divided into two main components: *composition* and *structure/configuration* (Li and Reynolds 1994). Composition describes the non-spatial attributes of the landscape such as number of patch types and the area of each patch type (Li and Reynolds 1994) which can have important spatial effects (Gustafson 1998). Structure describes spatial aspects of heterogeneity such as the arrangement and shape of patches as well as contrast of patch types between neighbouring patches (Li and Reynolds 1994). This study found that 93% of articles reviewed investigated composition aspects of landscape pattern and 59% investigated structural aspects (Figure 2.7). Only 5% of articles investigated structural aspects only, using methods such as graph based connectivity measures (e.g. Bodin and Norberg 2007).

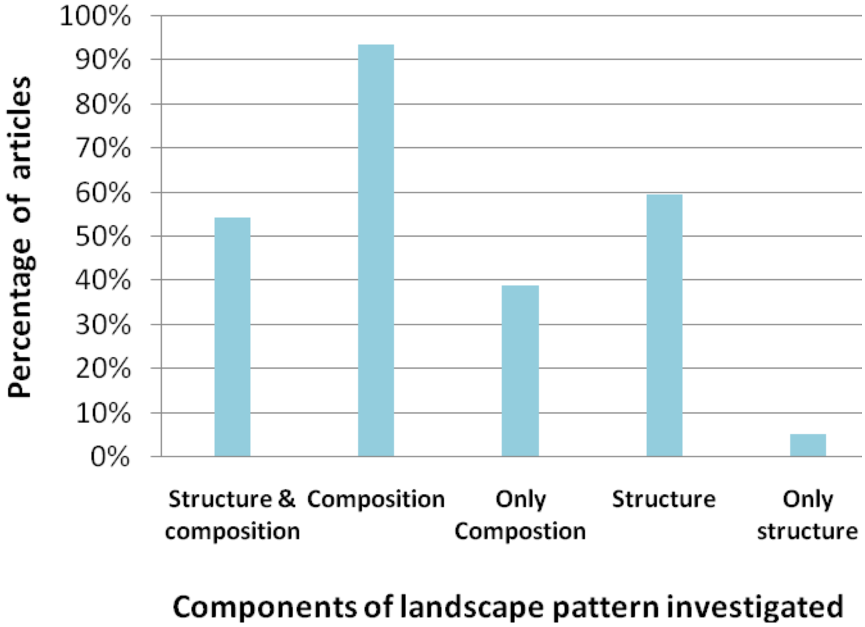


Figure 2.7 Components of landscape pattern investigated by the articles reviewed (n=59).

2.3.4 Pattern and process interactions

A core area of research in landscape ecology is understanding the mechanisms for creating and maintaining landscapes and the effect of landscape spatial pattern on ecological processes (Wiens 2002). Landscape pattern influences biotic processes such as the movement of organisms in the landscape (Ares et al. 2007) and abiotic processes such as the transfer of nutrients in a watershed (Saunders et al. 1991; Turner 2005). Conversely, the generation and maintenance of landscape pattern are influenced by a variety of processes such as economic forces, cultivation traditions, natural disturbances (Pickett and Cadenasso 1995) and ecological processes (Bartel 2000). Ecological processes such as colonisation by plant species will be influenced by landscape pattern but also influence the generation and maintenance of these patterns (Schröder and Seppelt 2006). The pattern-process relationship is complex, containing feedback loops, making it difficult to distinguish correlation from cause and effect (Nagendra et al. 2004). The pattern-process relationship may be the primary subject of research, such as in the case of studying the effect of fragmentation on ecological processes, or it may be a secondary consideration such as in the case of habitat modelling (Manton et al. 2005), conservation prioritization (LaRue and Nielsen 2008) and population viability analysis (Haines et al. 2006).

This review identified 4 main objectives/methods related to pattern-process interactions: 1) papers describing new methods related to measuring pattern such as the development of a new landscape metric (8%), 2) descriptive articles showing differences in landscape pattern (e.g. change detection) (7%), 3) spatial models investigating the effect of pattern on process (54%) and spatial models investigating the effect of process on pattern (29%)(Figure 2.8). Spatial models can explicitly represent the spatial location of variables, parameters or model interactions of processes directly (Wu et al. 2006) through modelling neighbourhood interactions or contagion (Urban 2005) (e.g. dynamic vegetation models such as LANDIS (Scheller and Mladenoff 2007)). Spatial models can also implicitly model landscape patterns indirectly through surrogates like the proportion of occupied habitat or a spatial pattern metric (Perry & Enright 2007). A common method of measuring landscape pattern throughout all the articles, both descriptive and those that use spatial models, was the use of landscape, class or patch metrics (often lumped together using the term landscape metrics/landscape pattern indices). In this review, approximately 31% of articles used landscape metrics, the most common spatial pattern metrics was number of patches and patch density. The widespread use of landscape metrics in landscape ecology is important as there are numerous studies that have demonstrated that landscape metrics are particularly sensitive to the effect of spatial uncertainty such as scale and classification (e.g. Buyantuyev and Wu 2007; Langford et al. 2006; Saura 2002; Wu et al. 1997).

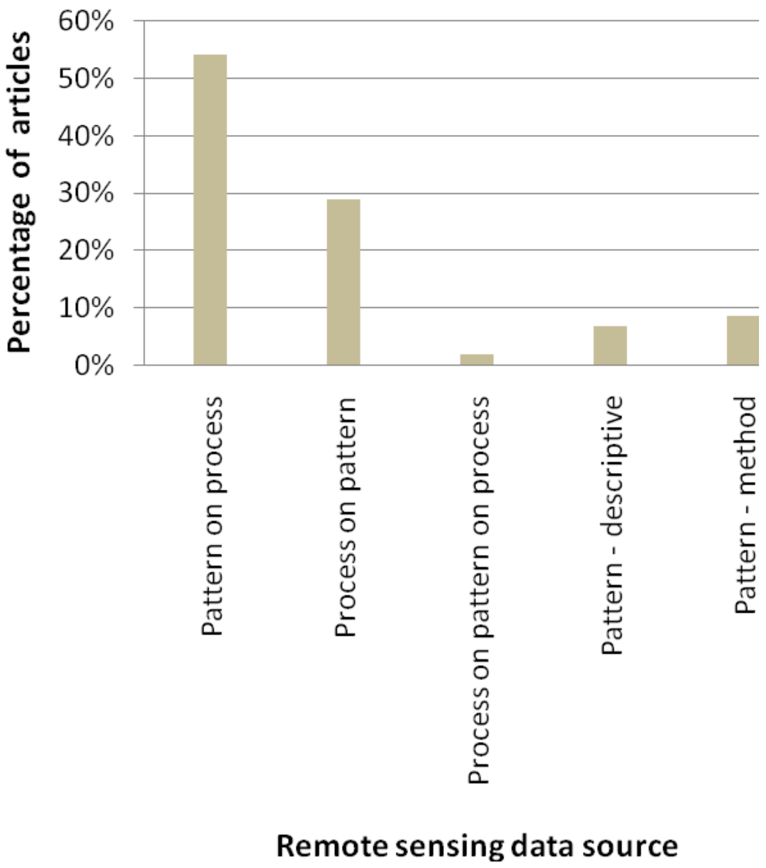


Figure 2.8 Main objectives/methods related to pattern-process interactions investigated in the articles reviewed (n=59). See above text for further information.

2.3.5 Landscape pattern and scale

The dependency of pattern-process relationships on scale is well documented and is the focus of considerable research effort in ecology (Levin 1992; Turner 1989). Both abiotic and biotic processes and natural and human caused disturbance interact with the environment on many scales to create spatial patterns (Turner et al. 2001). For example, abiotic factors such as climate, topography and geology affect the distribution of organisms at broad scales. While, ecological processes such as the movement of individuals between patches act at fine scales and can affect the distribution of organisms across broad scales. Pattern-process interactions change with scale and often in complex nonlinear ways (Li and Wu 2004; Wiens 2002). Thus, there is a need to incorporate and understand the effects of scale on ecological analyses.

There are a number of definitions of scale that vary between and within disciplines (Changyong and Lam 1997; Dungan et al. 2002; Goodchild and Quattrochi 1997; Schneider 2001). For example, within ecology, scale is considered to be both observational units (e.g.

Wiens 1989; Wu et al. 1999) and the scale at which resources are distributed across the landscape (e.g. Doak et al. 1992; O'Neill et al. 1988; Walters 2007). Scale as an observational unit can also have many meanings, such as grain or spatial extent (Mayer and Cameron 2003; Turner 1989; Wiens 1989). In this study the word *scale* is used as an overarching term that can be subdivided into three separate categories: *scale of the operation, scale of observation* and *scale of the analysis* (Dungan et al. 2002). The scale of operation (also known as scale of phenomenon or characteristic scale) describes the scale at which the phenomenon (i.e. an organism) interacts or perceives the landscape (Dungan et al. 2002; Wu and Li 2006a). The *scale of observation* (also known as sampling scale or measurement scale) describes the size, shape, extent and distance between observational units used to sample a phenomenon (Dungan et al. 2002; Wu and Li 2006a). In this study only the observation scale of the remote sensing data (e.g. pixel size) was considered and not the observation scale of ancillary data such as species observations. The *scale of the analysis* (or in some cases *modelling scale*) refers to the units that are used in analyses (Dungan et al. 2002; Wu and Li 2006a). Within landscape ecology the analysis scale is often patches or landscapes while the observation scale is the pixel size (Figure 2.9).

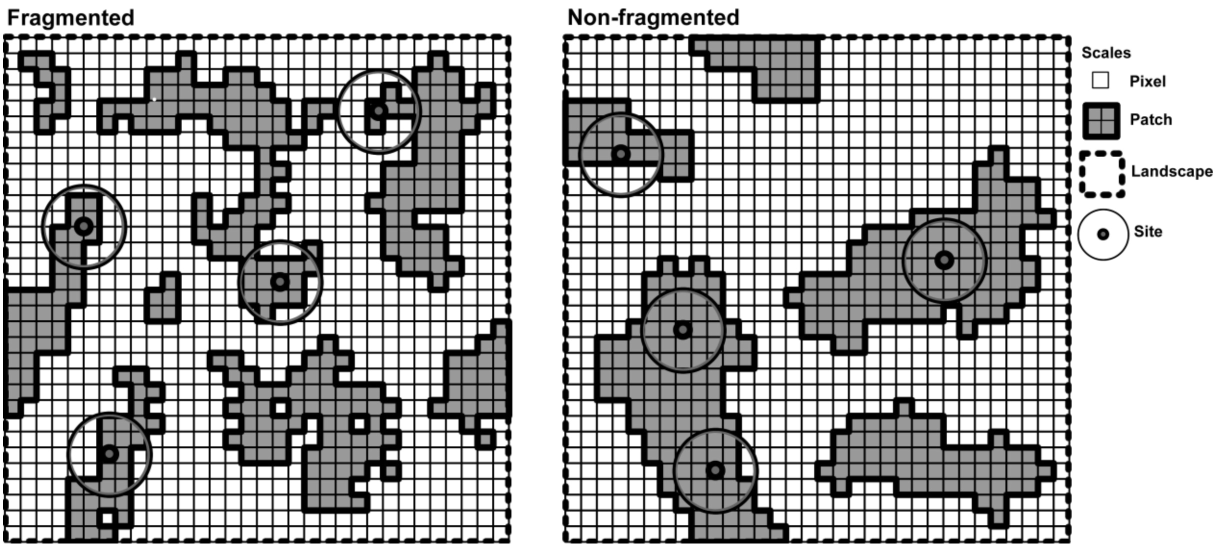


Figure 2.9 Example of different sampling and analysis scales used in landscape ecology. The observation scale may be a pixel, patch or site, while the scale of analysis may be a pixel, patch, site or landscape. For example, the number of patches (observation scale) may be calculated for each landscape (analysis scale) and a comparison of landscape pattern may be made between landscapes. Studies can be conducted at multiple analysis scales such as comparing within a landscape (e.g. comparison between patches) and between landscapes (e.g. average patch values per landscape).

The scale of the phenomenon is related to hierarchy theory, which describes the organisation of ecological systems into relatively isolated distinct operational scales (O'Neill et al. 1989). These scales operate simultaneously because biological systems are composed of interacting lower level components, nested within larger higher level systems (e.g. individuals are found within a population) (O'Neill et al. 1989). According to this theory, relationships found at one level are not necessarily transferable to another level, so each phenomenon needs to be measured at the appropriate scale (Turner et al. 2001). There may not be a single correct scale to measure a phenomenon and in some cases phenomenon act at multiple scales (Chen et al. 2008; Levin 1992; Wiens 1989; Wu et al. 2006). Thus, there is a need to measure and analyse at multiple scales in order to better understand the domains and interrelationship of scales at which ecological processes operate (Pontius et al. 2008; Wiens 1989). In some cases, the relationship between a phenomenon and its environment can be completely overlooked if the correct scale is not used (Saab 1997). Consequently, studies of the same phenomenon at different scales will usually lead to different results (Wiens 2002; Wiens 1989). Often it is not straightforward to determine the scale at which an ecological phenomenon interacts with the landscape, as little is known about this relationship (Holland et al. 2004; Mayer and Cameron 2003). This lack of knowledge greatly limits the effectiveness of ecological studies (Holland et al. 2004b). Some phenomena, however, may be scale invariant (Wu et al. 2006) or mathematically predictable and thus scalable (Saura and Castro 2007).

In practice, a phenomenon cannot be measured directly and our understanding of it is affected by the measurement method chosen. The relationship between scale of observation and analysis and understanding pattern-process relationships is complex (Figure 2.10). In studies of landscape ecology, uncertainty in the characterisation of the landscape is introduced by the use of remote sensing data. Remote sensing data represent landscapes as a field of rectangular (usually square) spatial units called pixels, where their size is determined by the sensor characteristics, data processing and/or GIS software. The pixel size is one of the many components that determines the scale of observation (Haining 2003). Thus, the characterisation of landscape pattern derived from remote sensing imagery is not only a property of the landscape itself but also the process of mapping the landscape (Brown et al. 2004; Hess 1994; Schmit et al. 2006)(Gergel 2007) (Figure 2.3). Fine scaled sampling resolution will obscure coarse grained landscape patterns; while coarse grained sampling will miss any fine scaled patterns as they become averaged out in larger sampling units. Landscapes may appear fragmented at one scale and continuous at another.

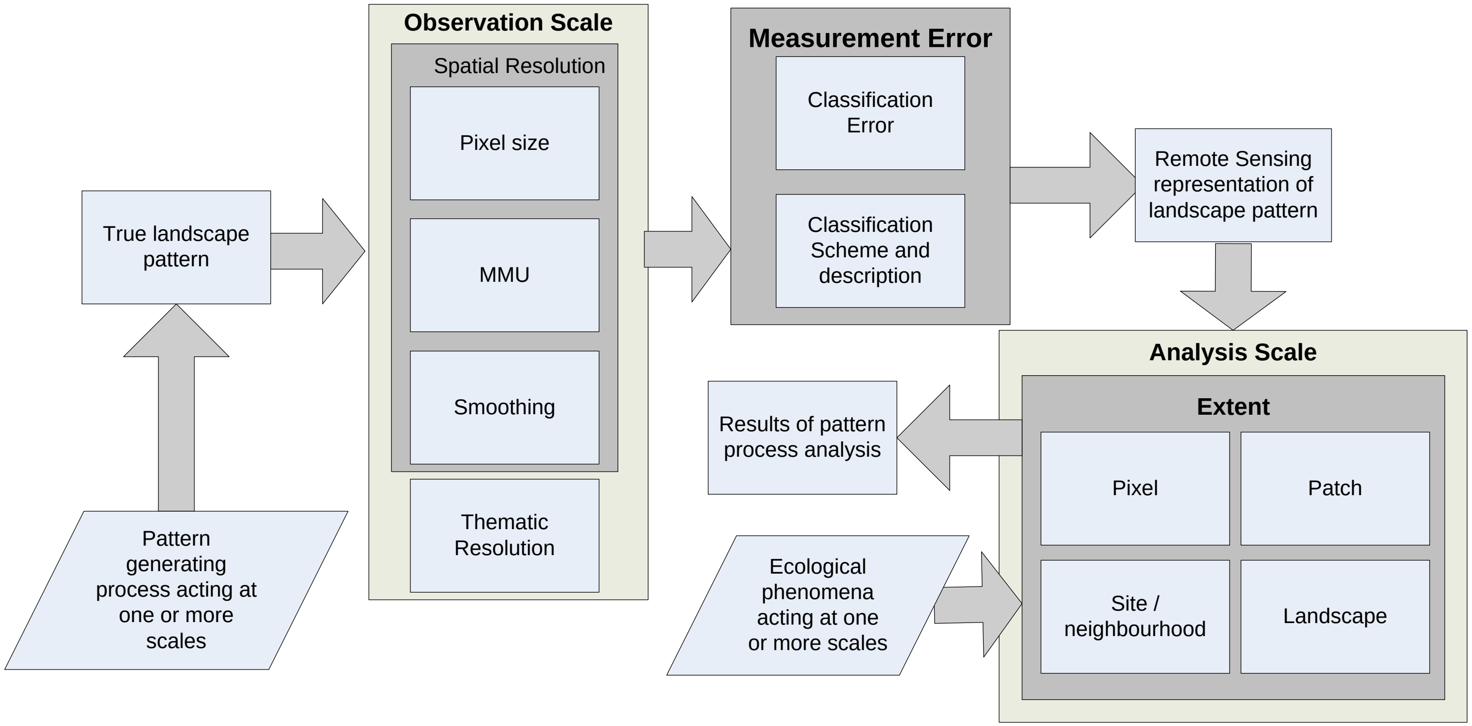


Figure 2.10 Conceptual relationship between scale of analysis and observation and the derivation of pattern-process relationship using remote sensing data.

The scale of the analysis refers to the scale at which data is analysed for inference and summarising (Dungan et al. 2002). When analysing spatial data the units of analysis in many cases will be the same as the observation scale, the pixel. In other cases the units of analysis will be derived from aggregating pixels to form new spatial units such as patches or landscapes. These analysis units need to be determined by the scale of the phenomenon being studied. Some phenomena have logical analysis units such as individuals per nest. Sometimes these units are hierarchical, for example leaves on a tree or trees within a stand. However, in many cases no logical analysis units exist (Dungan 2006), such is in the case of an ecosystem where the boundaries between different systems are fuzzy.

2.3.6 Observation scale and analysis scales

The scale of observation and analysis can change as a result of a number of different scale dependent factors relating to all aspects of the creation of spatial data, from the sensor used to post processing and analysis of data. The survey of the literature identified the following five scale dependent factors as important in determining the characterisation of landscape pattern in landscape ecology using remote sensing data. The first four factors affect observation scale: i) pixel size ii) minimum mappable unit (MMU), iii) smoothing techniques and iv) thematic resolution. The final scale dependent factor affects analysis scale: v) extent (Figure 2.10). Factors i–iv have similar effects on landscape pattern and are treated together. Together the scale dependent factors determine the limits of what can be mapped with remote sensing data.

2.3.6.1 Observation scale

The observation scale is made up of a subset of the scale dependent factors that affect the size and the information content of the sampling units. Spatial resolution is a product of several factors, including pixel size, minimum mappable unit and smoothing. The spatial resolution is the primary factor influencing the classification of remote sensing land cover data (Tatem et al. 2002; Woodcock & Strahler 1987) and limits the smallest identifiable area in an image (Tatem et al. 2002). In raw unprocessed raster data, spatial resolution is often considered to be equivalent to pixel size (Atkinson 2004). However, there is a subtle difference between the two; although the value of a pixel is predominantly determined by land cover corresponding to its location, it is also affected by land cover found in neighbouring pixels as determined by the point spread function of the sensor (Cracknell 1998; Fisher 1997). Thus, the true spatial resolution will be greater than the pixel size.

Furthermore, land cover found in the centre of a pixel has a proportionally greater contribution to its value than land cover found around the edge of a pixel. Other terms such as instantaneous field of view (IFOV), ground sampling distance, support and grain are sometimes used synonymously with spatial resolution, but all have subtle differences and ambiguities.

The area and shape of the sampling units will be a function of the smallest unit: the pixel. However, in some cases the smallest unit is greater than a single pixel as a result of classified pixels being aggregated into blocks of the same or similar value (Haining 2003). The smallest size of these blocks is considered the MMU. The MMU is quantified as an area or a number of pixels. For example, in the case of the CORINE land cover dataset of Europe the MMU is 25 hectares (European Environment Agency 1994). The imposition of a MMU occurs after an image has been classified into discrete classes most commonly by eliminating features smaller than a minimum size through reclassifying those pixels to the value of dominant neighbouring pixels. This technique is often used in binary landscapes such as in landscape ecology where smaller patches can be eliminated and replaced with the surrounding matrix. MMUs are often imposed to increase classification accuracy or increase legibility of the cartographic representation of the landscape (European Environment Agency 1994).

In a raw remote sensing image the MMU is the pixel size. The term MMU is often used to refer to the pixel size (e.g. Mayer and Cameron 2003; Turner 1989; Vermaat et al. 2005; Wiens 1989), however, I make the distinction between the pixel size and MMU, as they are not equivalent in regard to their effect on landscape pattern. For example, two maps may both have a grain size of 30 ha, but one map may have a pixel size of 30 ha while the other may have a MMU made up of 6 pixels with a pixel size of 5 ha. The two maps will characterise spatial pattern differently, as the second map with the smaller pixel size better represents fine scale fragmentation. Together, the pixel size and MMU affect the characterisation of landscape heterogeneity; as it decreases, within sampling unit heterogeneity increases and between sampling unit heterogeneity decreases (Dungan et al. 2002; Wiens 1989). The MMU tends to be larger than the pixel size so that spatial and/or content information may be lost (Fassnacht et al., 2006). Ideally the MMU or pixel size should be small enough to provide a representation of essential land cover elements. Where landscape elements are found as scattered small patches surrounded by matrix, the MMU and/or the pixel size should be smaller than patch size otherwise these patches would not be extracted. Conversely, if the MMU and/or pixel size is too fine it can result in a mismatch with biological data that may have been recorded at a much lower resolution (Chapman et al. 2005).

Both the pixel size and MMU define the area on the ground, where the sampling units are located, however, the value of the units do not coincide with value of the land cover on the ground. As stated above, neighbouring pixel values will contribute to the value of a pixel. Additionally, pre and post processing of a remote sensing image using smoothing filters or resampling will also increase the influence of the values of the neighbouring pixels, resulting in a reduction of spatial heterogeneity. Two common processes that smooth the image are the result of georectification and the application of a smoothing filter such as a low pass or majority filter (Figure 2.3). Smoothing filters are commonly used in remote sensing to increase global classification accuracy by decreasing the salt and pepper effect caused by per pixel based landscape classification schemes or to remove noise caused by sensor error in raw remote sensing data (Ivits and Koch 2002; Zukowskyj et al. 2001). Commonly, a majority filter is used during post processing for classified images (Lu and Weng 2007) and a low pass filter is used with raw data (Aplin et al. 1999). Another remote sensing technique that smoothes the image is resampling, often for geometric correction (georectification) or image registration (Cracknell 1998). Data from different satellites lead to differing orientations and locations of the grid due to the path of the sensor platform (e.g. aerial or satellite). Thus, images may be resampled to a common grid with a north south orientation. Data may also be resampled to correct for positional error (image registration). Finally, off-nadir rectangular pixels at the edge of images are usually resampled to a square grid before the user receives the data (Canty 2007). The resampling method used will have differing results. Nearest neighbour resampling simply rearranges the position of the pixels to the correct geometry while retaining the original pixels brightness values (Canty 2007). This method may cause spurious effects such as repetition or omission of pixels (Cracknell 1998). Other commonly used methods are bilinear interpolation and cubic convolution interpolation. These methods interpolate, and therefore will result in a mixing of spectral values between the neighbouring pixels (Canty 2007) and thereby smooth the image.

The final factor that makes up observation scale is the thematic resolution (Bailey et al. 2007; Buyantuyev and Wu 2007), describes the level of classification detail of the sampling units otherwise known as attribute precision (Cunningham 2006) or categorical resolution (Franklin and Woodcock 1997). The Anderson classification scheme is a classic example of a land use classification hierarchy that has many thematic resolutions (Anderson et al. 1976). The Anderson classification scheme contains 4 resolutions with each higher resolution class nested in a lower level class e.g. i) Urban or built-up ii) Residential iii) Single-family units. The exclusion or inclusion of different land cover classes will affect the representation of spatial pattern. Generally, when thematic resolution is high, landscapes will appear more fragmented (Buyantuyev and Wu 2007).

In the context of landscape ecology, observation scale (pixel size, MMU, smoothing factor and thematic resolution) are important in determining the characterisation and the accuracy of landscape components such as patches and corridors. Decreasing the resolution of the observation scale i.e. larger pixels, larger MMU, applying smoothing filters, and using low thematic resolution land cover classification schemes) all have similar effects on characterising landscape structure—reducing fine scaled fragmentation. This has been shown for each the factor: pixel size (e.g. Lechner et al. 2008; Wu 2004; Wu et al. 2002), smoothing (e.g. Lechner et al. 2008; Thompson and Gergel 2008), MMU (e.g. Kendall and Miller 2008; Prada et al. 2008; Shen et al. 2004; Stohlgren et al. 1997; Thompson and Gergel 2008) and thematic resolution (e.g. Buyantuyev et al. in press; Buyantuyev and Wu 2007; Castilla et al. 2009; Kendall and Miller 2008). When the resolution of the observation scale is low, small patches will not be extracted or aggregated into larger patches (Fassnacht et al. 2006; Lechner et al. 2008), the spatial extent and configuration of patches will change (Thompson and Gergel 2008), edge complexity will decrease (i.e. edge to area length decreases) (Kendall and Miller 2008) and landscapes will be represented as large homogenous areas that in reality may not exist (Corry and Nassauer 2005; Stohlgren et al. 1997). Ecologically important small and linear features such as corridors are more likely to be mapped inaccurately or be absent from an image compared to larger and more compact features (Lechner et al. 2009). Landscape composition is affected by all factors that make up observation scale; however, thematic resolution directly affects landscape composition though reducing the number of patch types (Corry and Nassauer 2005). Other factors that indirectly effect landscape composition through the loss of rare land cover classes tend to be found in small patches (Smith et al. 2002; Stohlgren et al. 1997; Thompson and Gergel 2008; Turner 1989). Thompson and Gergel (2008) found estimates of rare forest classes differed by as much as 36%, and that mean patch size increased by 650% due to the application of a smoothing filter.

The observation scale is not only affect the accuracy of remote sensing classifications (Smith et al. 2003; Woodcock and Strahler 1987) but also affect ecological analyses that use remote sensing data. Furthermore, traditional statistical methods are sensitive to the units of observation controlled by pixel size and MMU, and statistical significance will change according to the number observations (Pontius Jr et al. 2005; Stoms et al. 1992). Factors affecting spatial resolution (pixel size, MMU and smoothing) have been demonstrated to affect statistical analysis such as inference about population mean and variation (Pontius Jr et al. 2005). In cases where there are no natural units of observation, p-values will vary with scale (Levin 1992; Pontius Jr et al. 2005; Pontius et al. 2008). Changing scale can effect the output of ecological models such as multivariate analysis, by changing the variables included in a model, the relative importance of those variables and the complexity of the models (Andersson et al. 2009; Karl et al. 2000; Lawler et al. 2004). The effects of spatial resolution and to a lesser degree thematic resolution have been shown for other types of analysis such as measuring land cover proportions (e.g. Mayaux and Lambin 1995; Moody and Woodcock 1994; Smith et al. 2002), landscape metrics (Buyantuyev and Wu 2007; Corry and Nassauer 2005; Ju et al. 2005; Wu et al. 2000), graph based connectivity metrics (e.g. Pascual-Hortal and Saura 2007; Rae et al. 2007), statistical analyses such as bivariate and multivariate analysis (e.g. Bailey et al. 2007; Fotheringham and Wong 1991; Karl et al. 2000; Lawler et al. 2004), and change detection analysis (e.g. Pontius et al. 2008).

This review found most of the factors that made up observation scale were not addressed or reported: approximately 8% addressed pixel size, 2% addressed MMU, 5% addressed smoothing filter and 6% addressed thematic resolution (Figure 2.11). All of the studies that addressed observation scale conducted a sensitivity analysis to compare the effect of different spatial resolutions on their results. It was difficult to tell whether some factors such as MMU or smoothing filters needed to be addressed, as it was unusual for all the details of the remote sensing process to be reported.

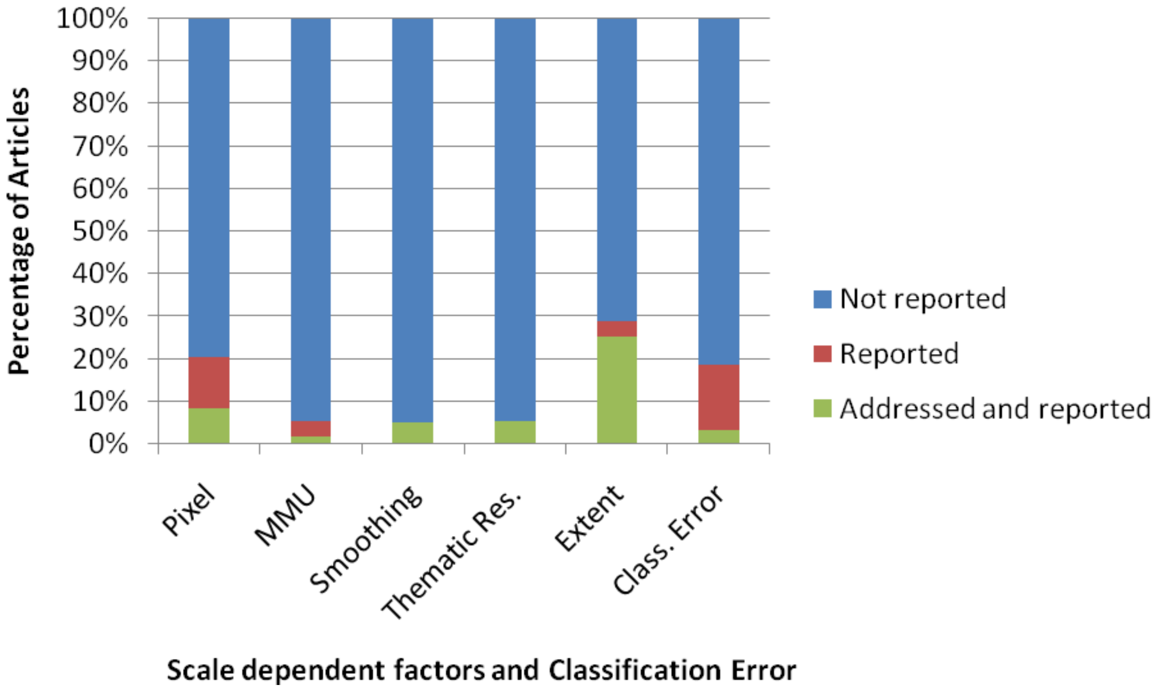


Figure 2.11 Scale dependent factors and classification error addressed, reported and not reported (pixel, smoothing, extent and classification error, n=59; MMU and thematic resolution n=54).

The scale dependent factors MMU and thematic resolution were only tested for thematic/categorical datasets that were used in 91% of the data articles reviewed. MMU and thematic resolution are not relevant to continuous data. MMU for continuous data is equivalent to the pixel size and thematic resolution can't be altered with continuous data as there is only a single category (e.g. greenness or tree height).

2.3.7 Scale of the analysis and extents

The scale of the analysis is a property of: i) the geographic extent of the analysis units and ii) the landscape components that can be measured with those spatial units (e.g. patches versus landscapes). The first component (i) is described by the scale dependent factor *extent* which refers to the size of the study area or the total area mapped (Gustafson 1998; Turner 1989). It is also known as geographic scale (Changyong and Lam 1997). The second component (ii) describes the spatial organisational level at which a study is undertaken e.g. patch, site or landscape-level (Lidicker Jr 2008).

Two broad scales are used to conduct analyses in landscape ecology: fine scale relationships of patches and their surrounds or coarse scale dynamics that investigate landscape as a whole (Pickett and Cadenasso 1995). Research investigating fine scale relationships mostly used either the patch or site organisational level (Figure 2.12). Studies that conducted patch-level analyses often compared patch measurements (e.g. patch area or shape) to ecological phenomena (e.g. species diversity) for each patch or a sample of patches within a landscape. Studies which used the site-level (i.e. core area or neighbourhood area or plot) analyses were often conducted by measuring ecological variables at a single point or plot (e.g. trap counts) usually found within a patch. These ecological variables were compared to environmental measurements calculated for the surrounding area usually within a circular buffer (i.e. percentage vegetation cover) (Debuse et al. 2007). The size of the neighbourhood area is commonly considered to be the grain size and should be related to the scale at which an ecological phenomenon operates (e.g. home range) (Mayer and Cameron 2003; Schooley 2006). Studies which use either the site or patch, are not strictly landscape scale studies, but rather patch scale studies conducted over a landscape. For studies with landscapes as the organisational level used for analyses, either multiple landscapes in different locations or the same landscape at different times were compared.

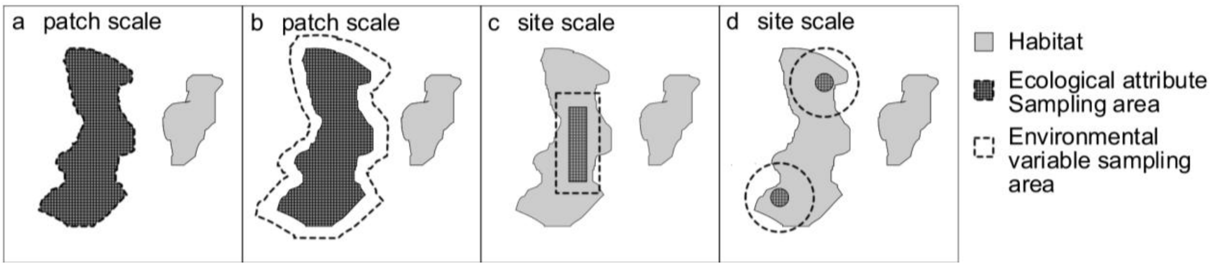


Figure 2.12 Examples of patch and site-level sampling designs using different spatial extents. a) Ecological variables sampled for the entire patch related to environmental variables such as area or shape for only the patch. b) Ecological variables sampled for the entire patch related to environmental variables calculated for the patch such as area and the area surrounding the patch such as land use. c) Ecological variables sampled in a plot such as using transect sampling and related to environmental variables in the surrounding area. d) Ecological variables sampled at a point such as trap counts related to surrounding environmental variables.

Throughout the articles reviewed there were a range of definitions used to describe analysis scales that differ from the above definitions. In this review, landscapes are considered to be an area composed of more than one patch (Figure 2.13). While other studies considered landscapes to be a single patch or plot and the area surrounding it, equivalent to this study's definition of patch and site-level (e.g. Coreau and Martin 2007; Davis et al. 2007; FitzGibbon et al. 2007; Gagné and Fahrig 2007). In many studies a single patch or plot and the surrounding environment is considered to be landscape scale. For example (Gagné and

Fahrig (2007) investigated the effect of landscape context on anuran communities in breeding ponds and defined landscapes as an area of 1.5 km surrounding an individual pond.

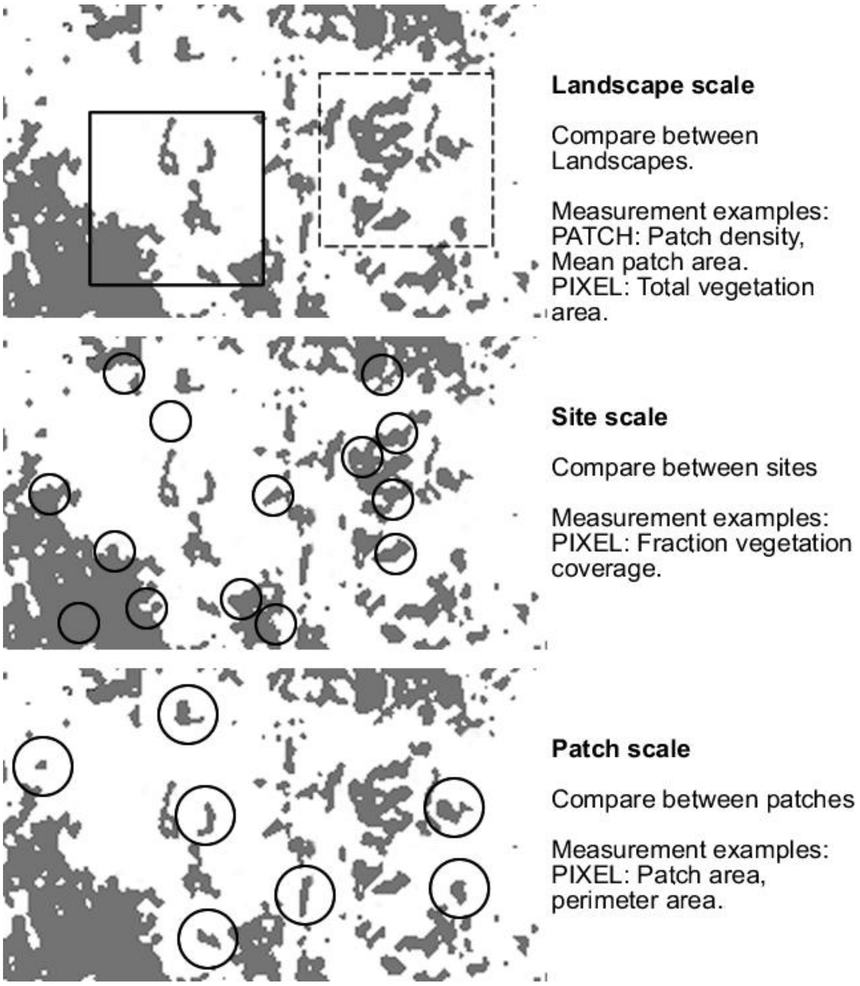


Figure 2.13 Examples of different organisational levels and the types of measurements used. Depending on the organisational level used, the types of ecological units (e.g. patches) that can be measured will differ. For example, at the landscape scale the number of pixels with certain values can be measured in order to calculate global area estimates or patches can be discretised and measurements can be based on these units (e.g. number of patches, average patch area).

This review found a range of organisational levels used to analyse ecological data. The most common analysis scale was the site scale 29%, while 22% used the patch scale and 53% used the landscape scale (Figure 2.14). In many of the articles reviewed, more than one analysis scale was used (e.g. Debuse et al. 2007; Gustafson et al. 2007).

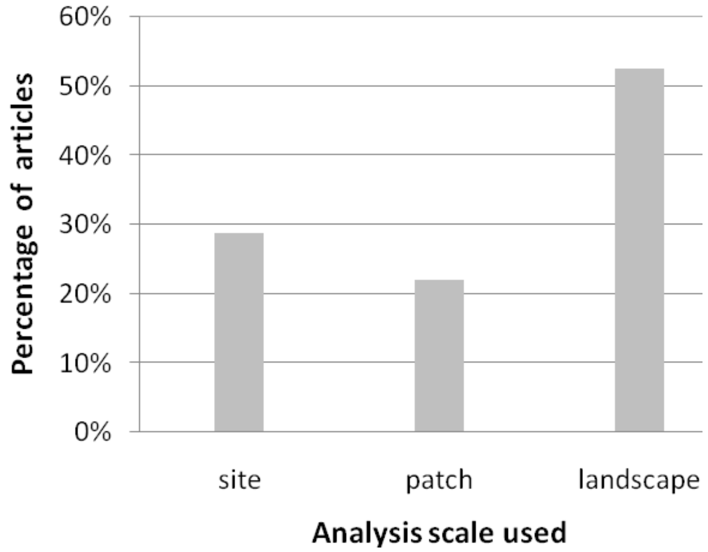


Figure 2.14 Percentage of articles using site, patch or landscape analysis scales. Note, some studies used multiple analysis scales.

Uncertainty associated with using specific analysis scales is a result of the sometimes arbitrary location of extent boundaries, affecting the characterisation of landscape pattern and the outcome of ecological analyses. Changing spatial extent affects observed ecological patterns; as extent increases so does the probability of sampling rare classes (Turner 1989; Wiens 1989). If pixel size is fixed, fragmentation increases with increasing extent (Riitters et al. 2000). Changing spatial extent can affect ecological analyses because it can influence the inclusion of abiotic and biotic processes that affect the ecological phenomenon in the study area. Broader scaled ecological processes such as atmospheric flows or climatic processes are only observable using large extents while small scale processes such as edge effect can be observed using smaller extents (Wiens 1989). Observable ecological processes will depend on the openness of the system being considered. For example, islands are closed systems with respect to the movement of ground dwelling animals, but can be considered open for the movement of birds.

Landscape pattern will change with extent, as landscapes may appear fragmented at one extent and continuous at other extents (Cushman and McGarigal 2008). The strength of the effect of extent on landscape pattern is dependent on landscape context. The effect of changing extent is be a property of the surrounding landscapes and is different if a fragmented landscape is part of a fragmented regional landscape or an abundant and continuous regional landscape (Cushman and McGarigal 2008). For example, Turner (1989) found that measures of diversity remained constant until the extent boundaries crossed natural boundaries (i.e. river, catchment boundary). Once the natural boundary was crossed, there was a rapid increase in diversity. Diversity then remained constant once more, with increasing extent until the next boundary was crossed.

Spatial extent can affect landscape pattern through artificially truncating patches that occur at the boundary (Cushman and McGarigal 2008; O'Neill et al. 1996). This can result in spatially continuous patches being divided up into smaller separate patches. As with the observation scale, changing extent will affect analyses such as measurements of landscape pattern (Buyantuyev et al. in press; O'Neill et al. 1996; Townsend et al. 2009; Turner 1989), graph based connectivity metrics (Pascual-Hortal and Saura 2007) and statistical analysis (Chapman et al. 2005; Hess et al. 2006; Wu et al. 1997).

This study found 29% of articles reported extent as an issue, and 25% attempted to address the problem. Testing for uncertainty in the scale of the analysis, where the organisational level was the site, was the most common form of spatial uncertainty addressed. It found that approximately 59% of studies that used the site organisational level addressed this form of uncertainty by modifying the size of the neighbourhood area.

2.3.8 Summary of the effects of scale

Only 8% of studies addressed grain (which includes either pixel size or MMU) and 29% addressed extent, which is low considering these two type of scale dependent factors appear to be the most prominent scale dependent factors discussed in the landscape ecology and ecological literature (e.g.Gustafson 1998; Mayer and Cameron 2003; Turner 1989; Turner 2005; Wiens 1989). Around 47% reported one or more scale dependent factors and 23% addressed one or more scale dependent factors; however, in most cases only a single scale dependent factor was investigated even though the multi-faceted nature of scale has been recognized (e.g. Lechner et al. 2008; Riitters et al. 1995). Wheatley and Johnson (2009) reviewed 79 multi-scale wildlife habitat studies published since 1993 and found that in addition to the initial scale chosen, which was biologically justified (i.e. home range size), the other scales tested, usually one larger and one smaller, were arbitrarily chosen.

Wheatley and Johnson (2009) also noted that many studies that claim to be multi-scale are in actual fact multi-design because they vary two or more scale dependent factors with only a single replicate of each and thus can’t demonstrate scaling effects (i.e. commonly varying both extent and pixel size at the same time). This is partly the result of the difficulty in separating scale due to practical reasons. This is especially true with regard to pixel size and spatial extent, which tend to vary together (e.g. a single scene of Landsat 7 TM with 30m pixels is 185 km in extent, while Quickbird 2 has 2.4 m multispectral resolution and an extent of 16.5 km). For the review I did not judge whether the scales chosen were appropriate; however, I found most studies were truly multi-scale not multi-design. In some cases, studies were wholly or partially multi-design measuring some or no scale dependent factors at all scales. For example, Coreau and Martin (2007) compared bird abundance measured at a sampling points to environmental characteristics measured in 25m, 50m and 200m buffer areas surrounding the points. In this study the same set of variables were not measured at all buffer sizes e.g. maximum vegetation height was only measured in the 25m buffer area and number of patches was only measured in the 200m buffer area.

This study found that 46% of the papers reviewed used Landsat data which has a 30 m pixel size for most bands of both TM and ETM+ sensors (only 1 of the studies used Landsat MSS which has a 60m pixel size) and 53% used aerial imagery with a pixel size less than 1 m (Figure 2.15). These finding are similar to a review by Vermaat et al. (2005), which found that Landsat was the most common sensor used in landscape ecology. I found most studies used the raw remote sensing image's pixel size except for those that specifically addressed scale issues and conducted multi-scale studies. The ubiquity of data from these two sensor platform suggests that the scales selected were arbitrary. The choice of an arbitrary scale goes against ecological thinking, which suggests that no single scale is appropriate for the study of all ecological problems. The results of this review confirm what other authors have pointed out: the choice of scale is often arbitrary and tends to reflect our own perception of nature rather than other species' perceptions (Wiens 1989). If scales are chosen arbitrarily, actual patterns and processes may become distorted (Wu et al. 2006). However, the results of this study differed from Vermaat et al. (2005), which reviewed the average spatial extent and grain sized used by studies in landscape ecology across all the ecological literature and found that the mean grain size was 880 m+/–300 m. This result suggests that ecological studies published in the journal of *Landscape Ecology* tend to focus on a subset of scales.

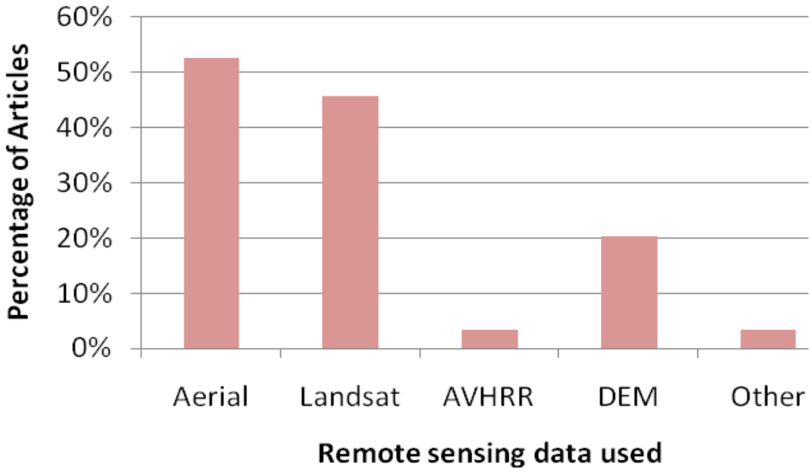


Figure 2.15 Percentage use of different remote sensing platforms for all studies (n=59). Note, some studies used more than one remote sensing dataset.

These findings are not surprising as the choice of scale is often driven by the available data and the cost in acquiring and classifying it (Chen 2008; Comber 2008; Fisher et al. 2005; Gergel 2007; Gustafson 1998). Low spatial resolution data is often bought because it costs less and is less computationally expensive (Hilty et al. 2006). The choice of spatial resolution represents a trade-off between constraints on operational costs and the provision of land cover requirements (European Environment Agency 1994). Higher resolution data such as aerial imagery can sometimes be more appropriate but are prohibitively expensive due to the high cost of flying and processing it (Gergel et al. 2007). For example, the European Environment Agency (1994) calculated the cost of acquiring imagery SPOT (HRV XS) (10 m spatial resolution) data to be 0.5 Euros/km^2 compared to 0.03 Euros /km^2 for Landsat TM and ETM+ (30 m spatial resolution). The influence of data availability on the scales used is in agreement with both Mayer and Cameron (2003) and Vermaat et al. (2005) who both conducted reviews of the scales used in studies of landscape ecology.

2.3.9 Ambiguity between ecological scale, scale of analysis and scale of observation

This study found considerable ambiguity in the use and the understanding of scale concepts and its causes in the articles reviewed. Firstly, the majority of articles used scale as a generic term but failed to qualify its explicit meaning as recommended in the literature (e.g. King 1991; Vermaat et al. 2005). This makes comparisons between studies difficult. For example, in one study scale was considered to mean spatial extent and in another it was considered to mean pixel size. Secondly, another fundamental issue arises from the ambiguity in interpreting the cause of the underlying scale dependent processes that affect ecological analyses. There are two well documented, inferred causes of finding differences in the results of ecological analysis due to scale: 1) the effects of the scale of operation (Levin

1992; Wiens 1989) and 2) the effects of the MAUP (Fotheringham and Wong 1991; Jelinski and Wu 1996; Wu 2004).

In order to assess the effect of scale for either of the above two causes, ecological analyses are conducted with data at more than one observation and/or analysis scale (e.g. multiple pixel sizes). Commonly, the effect of scale is assessed by differences in the strength of the statistical relationship between environmental explanatory variables represented with spatial data at multiple scales and an ecological response variable. In the first case, multi-scale analyses are conducted in order to find the scale of operation. The scale of operation is identified as the scale at which the relationship is strongest between an environmental variable and the ecological attribute. For example, an ecological study may try to identify the scale with the highest correlation between vegetation cover and species diversity. Ecological causes such as the effect of home range size and/or distribution of resources are then inferred as the underlying process that has caused the scale dependent patterns found in the analysis. In the second case multi-scale analyses are conducted in order to test for data sensitivity to the MAUP. In this case differences in the strength of the relationship, as a result of using different scales, indicate the existence of the MAUP. Thereby demonstrating that the results of an analysis may be unreliable. In both cases exactly the same analyses methods may be used but the inferred underlying causal process; the MAUP or scale of operation differ.

This review found that several articles used similar multi-scale analysis techniques, however, causality was attributed to either one of the contradictory effects. For example, Koper et al. (2007) used multi-scale analysis and indicated they were testing for the effects of MAUP, while Coreau and Martin (2007) also used similar multi-scale analysis methods and suggested they were investigating the scale at which the phenomenon interacts with the environment. Ultimately, experimental manipulation of the underlying processes is required to understand the causal effect as correlation does not imply causation.

2.3.10 Classification Error

While scale dependent factors are one type of spatial uncertainty in which the true scale of observation and/or analysis may be unknown, classification error refers to quantifiable error that is measured as the difference between the value recorded by a remote sensing map and the real value on the ground. Error is generated at different stages of the production of remote sensing maps, affecting the representation of land cover (Friedl et al. 2001). The sources of error can be found in the remote sensing model and the processing of that data. The remote sensing model is composed of three components: i) the scene model, which describes the spatial and temporal characteristics of land cover, ii) the atmospheric model, which describe the effect of atmosphere (e.g. clouds) and iii) the sensor model, which describes the how the sensor takes spectral measurements (Strahler et al. 1986).

The statistical analysis of classification error is conducted using an error matrix also known as a confusion or agreement matrix and is considered fundamental to accuracy assessment (Congalton 1988; Foody 2002). The confusion matrix describes the accuracy of each land cover class and the nature of the confusion between the classes statistically (Congalton, 1991). Studies that make use of a remote sensing land cover dataset should as a minimum include an accuracy assessment (Cunningham 2006). However, this review found that only 5% of studies included a confusion matrix.

High accuracy biophysical input maps derived from remote sensing are considered important requirements for ecological models such as predictions made by habitat models (Guisan and Zimmermann 2000). There is no universal standard of acceptable classification accuracy for thematic maps. Often, targets are not stated explicitly; however, 85% is a value often quoted (Foody 2006). Even if an error matrix records an overall accuracy greater than 85% there is no guarantee that the error assessment is accurate as there is considerable uncertainty in their generation (Chen and Wei 2009; Congalton and Green 1993; Stehman and Czaplewski 2003). Furthermore, as classification error is not randomly spatially distributed across the landscape (Congalton 1988) the standard error matrix is not suitable for the assessment of error in the representation of spatial pattern. Hess and Bay (1997) concluded that the present method for assessing spatial accuracy does not allow for the assessment of the sensitivity of landscape metrics to error. Classification errors can be magnified when propagated into a model (Gergel et al. 2007). For example, Langford (2006) found that in certain situations classification error can cause a thousand-fold increase in error in the calculation of landscape metrics. There are however no standard methods for quantifying the spatial distribution of error (McGwire and Fisher 2001). Gergel et al. (2007) suggested that it is important to describe not only the magnitude of errors but also the implication of the errors. My review found only 1 of the articles reviewed tested for the effect of classification error on analysis.

2.3.11 Interactions of scale dependent factors, classification error and landscape context

Both classification error and each of the scale dependent factors interact to affect landscape pattern characterisation (e.g. Kendall and Miller 2008; Langford et al. 2006; Lechner et al. 2008; Shen et al. 2004). Thus, testing of multiple scale dependent factors is recommended as these interactions need to be considered (Lechner et al. 2008; Shen et al. 2004). Classification error, for example, does not occur independently of scale. It has been shown that degrading the spatial resolution may result in higher classification accuracy in particular landscapes (Townshend and Justice, 1988). Langford et al. (2006) showed that the common practice of decreasing classification error through increasing MMU can sometimes result in an increase in errors in the calculation of landscape metrics. However, the testing of more than one scale dependent factor or classification error and a scale dependent factor was unusual, occurring in 1 of the papers reviewed.

The interaction of scale dependent factors and classification error is also affected by landscape context, such as the level of spatial autocorrelation. The spatial distribution and composition of landscape features changes the way that these factors affect the characterisation of landscape pattern. For example, as grain size increases, rare land cover classes tend to decrease; however, this decrease is slower when land cover classes are clumped than when they are dispersed (Turner 1989). In highly fragmented landscapes certain land cover types need a higher spatial resolution in order to accurately classify them (Smith et al. 2003; Soares et al. 2008). Land cover classes that tended to be linear or found in isolated patches disappeared as pixel size increased and overall the number of classes was reduced. Thus, using higher thematic resolutions at finer scales may be impossible in some landscapes (Rocchini 2005).

2.3.12 Addressing spatial uncertainty in ecological analyses

In order to conduct robust ecological analyses the impact of spatial uncertainty arising from classification error and scale need to be considered. The most commonly used method of addressing spatial uncertainty found in the papers reviewed was a sensitivity analysis (Buyantuyev and Wu 2007; Vogt et al. 2007a). Sensitivity analyses are recommended in order to understand how spatial uncertainty behaves propagates in ecological models (see Jager and King 2004; Jager et al. 2005). Sensitivity analyses are conducted by evaluating the results of a model multiple times with alternate realisations of the input data. Alternative realisations are generated either systematically or using the Monte Carlo method (Heuvelink 2002) whereby they are randomly generated using an error probability distribution.

A sensitivity analysis is one method of addressing issues of scale (e.g. Heuvelink 1998); however, a most important first step when addressing scale issues is identifying the scales at which a phenomenon operates thus ensuring a study is conducted at the appropriate scale (Gustafson 1998; Levin 1992). The scale of observation and analysis should be based on empirical knowledge or through an exploratory analysis (Wu et al. 2006). One recommendation is to find the scale at which maximum variability of the data occurs in order to determine the appropriate scale of analysis (Changyong and Lam 1997). This is type of method is often proposed within the remote sensing community. Detecting the appropriate scale of analysis involves using techniques such as finding the scale at which the highest average local variance (e.g. Woodcock and Strahler 1987) or the highest fractal dimension (e.g. Lam and Quattrochi 1992) occurs. In ecology studies are often conducted at multiple observational and/or analysis scales in order to provide an understanding of the dominant scales or to test the robustness of an analysis to scale (Mayor et al. 2007; Turner 1989; Turner et al. 2001; Wiens 1989; Wu et al. 1997). Testing at multiple scales is important as often there is little known about the scales at which species respond to habitat heterogeneity (Holland et al. 2004).

Multi-scale studies should be conducted at a continuum of spatial scales as opposed to a few subjectively selected scales or hierarchical levels to ensure that the study is indeed multi-scale not multi-design (Mayor et al. 2007; Wheatley and Johnson 2009). Analyses at multiple scales need to cover a range of scales that affect the ecological phenomenon being investigated. It can be difficult however, to make assumptions about the effects of changing scale on the characterisation of fragmentation as any form of aggregation of the scale dependent factor will result in range of effects on the various components of landscape pattern. For example, Saura (2004) investigated the affect of aggregation on the quantification of landscape pattern with a range of landscape metrics and found most metrics indicated lower fragmentation at coarser spatial resolutions. Saura (2004) found power scaling-laws between aggregation level and several landscape metrics. In other cases phenomenon are scale invariant or behave linearly with scale whilst measurements of spatial pattern for other phenomenon exhibit a staircase-like pattern of change with increasing scale indicating that pattern forming processes may operate at different breakpoints (O'Neill et al. 1999; Shen et al. 2004). While scaling relationships between landscape patterns and landscape metrics have been found, they are study specific and reliable well-tested scaling universal laws do not exist (Gergel 2007).

Conducting multi-scale studies are limited by landscape characteristics, practical limitations and data constraints (such as the availability of spatial data and geographic extent). Analysis methods need to be tailored to the spatial characteristics of the landscape (Gustafson 1998). For example, a landscape that is difficult to apply a categorical discrete classification to will produce a high uncertainty in the characterisation of landscape pattern. Testing may also be limited by practical considerations. For example, fine scale testing is limited by the availability of fine scale data and at broad scales by the available geographic extent.

In cases where appropriately scaled data is unavailable, one option is to extrapolate across scales. However, scaling across heterogeneous ecosystems remains a challenge (Levin 1992; Wu and Li 2006b). This type of scaling can be complicated by critical non-linear thresholds in the relationship between ecological phenomena and landscape pattern (Gardner et al. 1989) affecting the outcome of spatial analysis (Heuvelink 1998). There are multiple methods for transferring information between scales (Wu and Li 2006b) (cf. Wu and Li 2006b for a review of methods). Scaling relationships have been demonstrated for certain classes of landscape metrics following the power law (Saura 2004; Wu et al. 1997). However, these scaling relationships may be complicated by the choice of explanatory variables, the idiosyncrasy of particular landscapes, the nonlinearity of scaling relationships and an ecological model that may depend on data at particular scales (Heuvelink 2002; Heuvelink et al. 1989; Li and Wu 2004; Wu et al. 1997).

2.3.13 Other sources of error

The types of spatial uncertainty that were investigated in this review were limited to classification error and scale dependent factors because they are consistently cited in the literature as having significant effects on spatial analysis in landscape ecology. However, there are many other issues that were not investigated relating to the creation and use of remote sensing datasets in spatial analysis: from pre-processing, classifying, post-processing, associating remote sensing data with ancillary data to modelling data (Haining 2003; Worboys 1998). Although not an exhaustive list, some examples of spatial uncertainty that was not reviewed include: (i) Positional errors which are a result of a discrepancy between the map location and the true location on the ground (Haining 2003); (ii) Errors associated with linking remote sensing data with ancillary data resulting from inaccurate positioning of ground sampling points such as species occurrences (Laurent et al. 2005; Leyequien et al. 2007; McKelvey and Noon 2001) or scaling errors where the data at the sample plot level are up-scaled to remote sensing data (Wu and Li 2006a); (iii) GIS operation errors such as those associated with transferring between different GIS models (i.e. raster to vector) (Holland et al. 2007; Wade et al. 2003) and overlaying datasets to create new data (Arbia et al. 1998; Linke et al. 2009); (iv) Analysis error originating from the choice of particular forms (equations) or components (variables, covariates), statistical confidence in variable estimation, sample sizes, variability inherent in ‘natural’ systems, statistical assumptions like independence of spatially autocorrelated data not being met (cf. Karl et al. 2000; Peters and Herrick 2004; Schooley 2006). In most cases, the complete process of spatial analysis was not reported. Thus, it was impossible to assess whether these sources were ignored or not. It is assumed, though, that these other sources of error were also not addressed in the majority of studies.

2.4 Conclusion

This review confirms the concerns of other authors that the assumptions, generalisations, and error that occur when using spatial data are not being addressed by ecologists (Chapman et al. 2005; Nelson 2001). The complexity of the remote sensing data creation process and difficulties in incorporating spatial uncertainty into ecological analysis mean that addressing these issues is a non-trivial task. In many cases landscape ecologists lack the necessary skills to create spatial data and/or understand the creation process as they often only deal with the final remote sensing product such as a generic land cover map (Adams and Gillespie 2006; Schmit et al. 2006; Turner et al. 2001; Wiens et al. press). The difficulties of addressing these issues are further compounded by the lack of clearly defined rules for dealing with spatial uncertainty when developing ecological models (Chen 2008).

There has been an awareness of the serious implications of spatial data uncertainty on ecological analysis since the 1950s (e.g. Yule and Kendall 1950). This review clearly shows that these issues are being largely ignored by landscape ecologists—the branch of ecology where spatial data is a fundamental input into ecological models. It suggests that the scale of observation is increasingly being driven by the limited spatial scales used by satellites. In many cases, readily available datasets are employed without an understanding of the assumptions and rules used to create the dataset. The lack of importance given to spatial uncertainty in landscape ecology is exemplified by the many articles reviewed that failed to document the source of the spatial data and the processing used.

The majority of papers that addressed scale issues were primarily investigating issues of scale; that is, scale is not being addressed as a matter of course. In most cases, authors failed to acknowledge the existence of spatial uncertainty issues; using the raw remote sensing image's pixel size. In some cases, it is possible that the scale of the dataset may have been appropriate for the organism/s in question by default, or that the classification error levels may have been low enough not to affect analyses. It is also possible that some authors may have failed to write about these issues due to space requirements, even if they had been explored as part of a rigorous scientific method. However, I believe that the overwhelming weight of evidence dictates a need to address scale and error explicitly and that the acknowledgement of these issues should be standard practice. Standard practice for articles that conduct spatial analysis should include a definition of scale, an explanation of the scale dependent factors associated with the data (i.e. MMU, spatial extent etc), and an inclusion of an error matrix and a description of the scale at which the ecological phenomenon perceives the landscape. Finally, a sensitivity analysis should be a minimum requirement.

This chapter has drawn together ample evidence demonstrating the impact of spatial data uncertainty on ecological analyses. Landscape ecologists cannot assume that their analyses are immune to these influences and must develop methodologies for testing, understanding and dealing with the effects of spatial uncertainty. In order to address spatial uncertainty in landscape ecology fundamental research is needed to understand how scale affects the characterisation of landscape pattern especially with respect to the identification of ecological important landscape elements. Furthermore, there is a need to understand how the scale dependent factors interact with each other using quantitative analyses to provide generalisations and rules. Lastly, the underlying processes that cause spatial uncertainty—the scale of the phenomenon and MAUP—need to be understood.

Chapter 3 Remote sensing of small and linear features: Quantifying the effects of patch size and length, grid position and detectability on land cover mapping

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3.1 Introduction

The use of remote sensing imagery for the creation of land use and land cover maps is common place within landscape ecology and natural resource planning (Antrop 2007; Hilty et al. 2006). Thematic maps derived from remote sensing imagery can be used to characterize landscape structure and composition and relate these to landscape processes (Metzger 2008) such as species migration (e.g. LaRue and Nielsen 2008) or landscape change (e.g. Nagendra et al. 2006). Features such as small remnant and linear vegetation patches have ecological value that is proportionally greater than their areal extent. The presence or absence of these features change landscape pattern related properties such as connectivity and degree of fragmentation. Of key importance is an understanding of the process of mapping these patches. This paper simulates the process of classifying small and linear features, which allows for a basic understanding of the appropriate spatial resolution required to extract these patches when mapping using remote sensing imagery.

Small and linear vegetation patches are ecologically significant and can be found as roadside vegetation, hedge rows, scattered trees, riparian areas and greenways or are purposely built to facilitate connectivity (Bennett 1990; Gergel et al. 2007; Hilty et al. 2006; Manning et al. 2006). In rural landscapes trees and hedgerows are important biological and ecological components and function as windbreaks, field boundaries, erosion control, as well as for ecological and biodiversity value (Thornton et al. 2006). Small and linear vegetation is also important for wildlife habitat and can function as wildlife corridors which have been shown to have a positive effect on biodiversity and species persistence (Suter et al. 2007). The accurate mapping of wildlife corridors is essential as physical attributes of corridors such as width and length can affect the use of corridors by wildlife (Hilty et al. 2006; Lindenmayer and Fischer 2007). However, it is due to the relatively narrow width of corridors that they may be under-represented in the landscape when mapped using remote sensing (e.g. Vogt et al.

2007b) or traditional field based mapping. The accurate mapping of linear vegetation is key to the development of ecological models as such habitat suitability models. Land cover and vegetation maps which do not accurately represent the size and/or number of patches are a source of uncertainty within spatially explicit models (Minor et al. 2008).

Of great importance to map users interested in these small and linear vegetation patches is estimating what is the smallest discernable feature at any given spatial resolution and the accuracy at which these features are mapped. To the best of our knowledge, formal rules do not exist for describing the appropriate spatial resolution required. This is likely caused by the complexity of the problem, as the classification technique, landscape features, desired land cover classes and sensor resolution and characteristics will all affect the outcome of a classification (Lu and Weng 2007). Appropriate areas or dimensions required in order to extract features have been suggested, described in terms of pixels for measurement purposes, as in this study. The pixel traditionally represents the smallest discernable feature (Tatem et al. 2002) and limits the size of the feature that can be extracted (Aplin 2006). Estimates of the smallest discernable feature vary. According to Hengl (2006), at least four pixels are required to detect the smallest objects and at least two pixels to represent the narrowest objects. Cracknell (1998), however, suggested that we can detect an object which is of comparable size to the instantaneous field of view (IFOV) of the sensor. Regarding the detection of small and linear vegetation features a reasonable consensus exists; less than 4 to 5m spatial resolution is required. Jensen and Cowen (1999) concluded that high spatial resolution imagery between 0.25 to 10m is required for environmentally sensitive habitat in urban areas where vegetation is found in patches as small as median strips and backyards. Lausch and Herzog (2002) suggested that spatial resolution should be below 5m to capture linear features such as wildlife corridors. Finally, Congalton et al. (2002) suggested that sensors with finer spatial resolutions such as IKONOS with 4m multispectral sensor will be more appropriate for features with smaller areas such as riparian vegetation.

Previous research on the appropriate spatial resolution for mapping small and linear objects is mainly based on qualitative examinations. So far, a proper quantification with probabilistic tools, however, is missing. Extraction probability and classification accuracy is a function of the size, shape and the random position of a feature with respect to the sensor array's grid (Figure 3.1). Additionally, they are a function of both its spectral characteristics and those of the surrounding objects. This study extends previous qualitative investigations by simulating imagery in order to model the sub-pixel location of features with respect to the grid; testing the effect of grid position, contrast and feature size and shape in isolation. However, classification will be affected by other factors such as image registration, view angle, radiometric calibration, image acquisition time and sensor characteristics such spatial and radiometric resolution and bandwidth (Cracknell 1998; Townshend et al. 1991). Thus classification accuracy and extraction probability as calculated in this study is the result of the geometric properties of the grid alone, representing the best case scenario for remote sensing where the above factors are ignored. The aim of this paper is to: 1) determine the effect of the position of the raster grid in relationship to small and linear landscape features on classification, 2) provide a basic understanding of the appropriate spatial resolution required to extract features of various degrees of elongation and area and 3) examine the effect of differing spectral contributions of the object and its surrounds on classification.

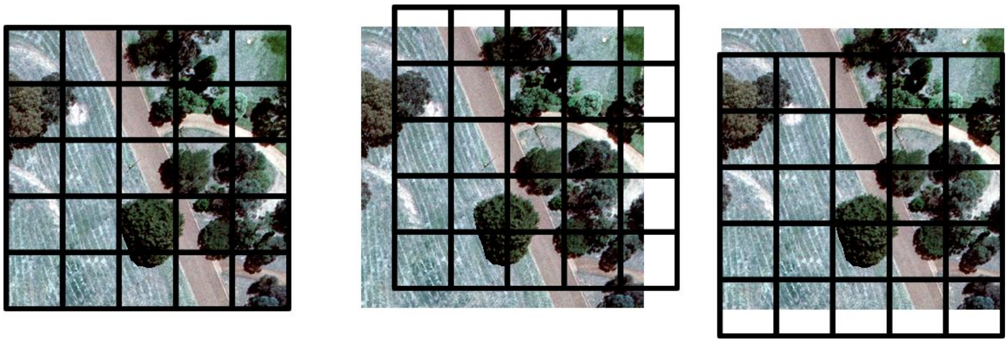


Figure 3.1 The position of a satellite sensor array's grid is random with respect to features in the landscape. An example of 3 different possible positions of the grid out of an infinite number of possibilities. Notice the location of the darker larger tree (centre bottom). Classification of the tree will be more accurate when it is located in the centre of a pixel as opposed to the intersection of many pixels.

3.1.1 Background to the problem

Rough single figure estimates do not recognize the effect of the random location of the sensor array's grid with respect to the feature. The lack of recognition of this random effect is common, as when using the traditional hard classifiers (which have one class per pixel) the unstated assumption is that land cover fits well into a grid consisting of square shaped spatial units (Fisher 1997). As features will not generally be placed to match the position of the grid, this can result in small features being lost when they only make up a portion of a cell or are found at the intersection of several cells (Cunningham 2006; Wehde 1982). The grid position effect can be a significant source of mapping error for individual map features (Wehde 1982). Cunningham (2006) noted that winding river channels of ecological importance can easily be lost in this way using 30m Landsat imagery. Problems of this type are particularly common in highly fragmented environments such as urban and peri-urban areas. For example, Australian road side vegetation can be around 2 to 4m wide, whilst high spatial resolution satellites such as Quickbird and SPOT XS have a multispectral spatial resolution of 2.4m and 10m respectively.

Other factors that contribute to the misclassification of small and linear features are its local contrast with the surrounding objects and the objects contribution to the pixel's spectral signal (Hengl 2006). When pixel to pixel contrast decreases, the target will ultimately be below the detection limit resulting from measurement uncertainty (Adams and Gillespie 2006). Detectability is scene and sensor specific (Adams and Gillespie 2006) and decreases with increasing spectral similarity between target and surrounding objects (Forshaw et al. 1983) and sensors' sensitivity. Another spectral factor contributing to misclassification is the difference in physical area of the target object with respect to its information class. A hard classification often assumes that the class occupies the majority of the area of the pixel (Fisher 1997). However a tree with a sparse canopy, for example, may consist of 30% leaf area, whereas the boundary of the information class tree is the perimeter of the canopy. A pixel may thus be classified correctly as a tree even if it covers less than 30% of the pixel area.

The investigation of the smallest discernable feature focuses on the instance where the size of the feature and the grid are similar. Strahler et al. (1986) developed the L & H resolution model that describes the relationship between the size of objects in a scene and the pixel size. H-resolution is the condition where objects are larger than pixel size (Woodcock and Strahler 1987). Whereas L resolution is the condition where land cover objects are smaller than pixel size (Woodcock and Strahler 1987) and only detectable as part of a mixed pixel and not as individual objects (Lu and Weng 2007). Objects need to be several times smaller or larger than the spatial resolution in order to regard the scene model as either H or L resolution (Strahler et al. 1986). This study is at the interface between L & H resolution, where it is difficult to define a land cover class using either object model. However, we treated the scene as H resolution, as only single features are tested. At the scale of this study the probability of a single feature being classified or extracted correctly is a function of its shape, grid size and its location. Classification accuracy decreases from 100% if the feature is of the same size as the grid and its classification is based on the majority rule (Figure 3.2a) to lower values when the grid does not align with the feature's shape (Figure 3.2b-e).

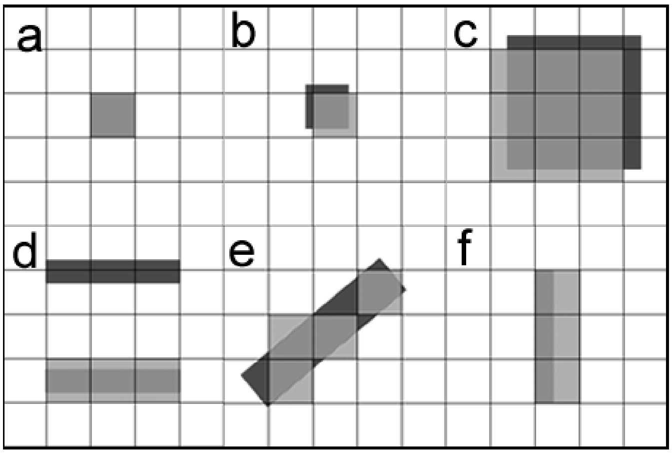


Figure 3.2 Features size and shape in relation to the grid. (a) Feature position, size and grid position result in a perfect match. (b) Perfect match with feature dimensions and grid size, but imperfect match with the grid position. (c) As *b*, but a lower error due to the larger number of interior pixels. Interior pixels have 100% accuracy for any grid positions. (d) The position of the grid is important when objects are of a similar size to the grid. Objects can disappear and appear because of its position. (e) Larger errors due to differences in orientation and position. (f) The feature's relative contribution to the value of a pixel is high resulting in a greater likelihood of being extracted.

To demonstrate the patch size, shape and grid location phenomena we carried out a qualitative analysis using real multispectral images from an area northwest of Melbourne, Australia. A 15cm near infrared aerial image (Figure 3.3a,c,e,g) captured in 2005 was classified by thresholding a derived normalized difference vegetation index to generate a vegetation versus non-vegetation land cover classification. This was compared with a similarly classified 10m SPOT XS image captured in 2004 for the same area. The aerial photography was geometrically registered to the SPOT image using ArcGIS (ESRI 2007b). Subsets of the area with linear vegetation and/or small patches of vegetation of the total scene were clipped. Clips were taken from locations within the images near NADIR. The images were then overlayed to examine the differences in classification.

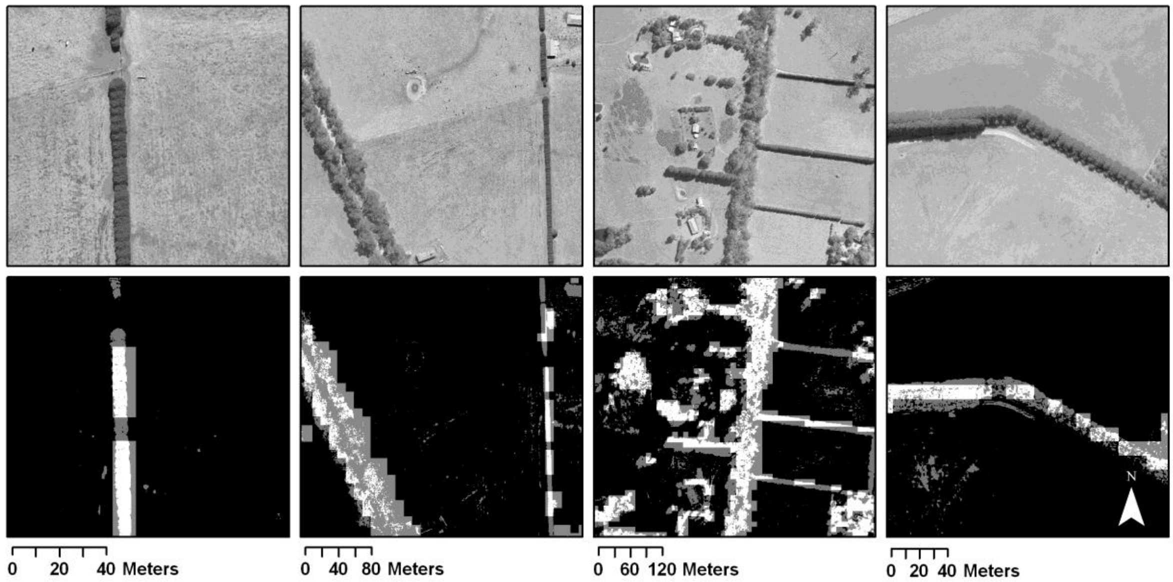


Figure 3.3 Top row: 15 cm georeferenced NIR Aerial taken in 2005 for the North West Melbourne (Australia) with a spatial accuracy of 1–2.5 m RMSE (68% Confidence). Bottom row: above classified aerial imagery overlayed with transparent orthorectified 10 m classified SPOT XS imagery with a spatial accuracy of 12 m. White areas: both classified aerial and SPOT imagery identified vegetation; Gray areas: SPOT and aerial imagery differed in their classification of vegetation; Black areas: both SPOT and Aerial have not identified vegetation.

Figure 3.3b shows some linear vegetation patches appearing to be discontinuous in the SPOT image. This could be the result of the width of the linear strip decreasing so that at certain points it occupies less than 50% of the pixel area. Figure 3.3d demonstrates a similar phenomenon as figure 3.3b. Notice, however, that the large linear strip of vegetation in the west of the image has a width greater than a single pixel and is classified correctly in comparison to the narrow linear strip to the east which is incorrectly broken into a series of patches. Figure 3.3e shows 3 similar linear strips of vegetation (paddock boundaries). Figure 3.3f illustrates that they have all been mapped differently. The most northerly has been omitted (i.e. not mapped). The middle strip mapped more or less correctly and the most southerly is broken into a series of islands or patches. This is the result of the strips' location and orientation to the grid. Figure 3.3h demonstrates that as a linear strip changes orientation the effect of the position of the grid well result in differing classification accuracy.

3.2 Method

We developed a statistical simulation model to test the effect of patch size and shape, classification threshold and grid location on the classification of small and linear features using remote sensing data. To simplify the investigation a binary hard classification was used; patch vs. matrix. This type of classification scheme is used in ecology, for example, to describe the patch-corridor-matrix model (Forman and Godron 1986) fundamental to landscape ecology (Antrop 2007) and is often applied to tree presence/absence datasets (e.g.Vogt et al. 2007b).

A computer model considered rectangles of a variety of lengths, widths and total areas with different classification thresholds and orientations to simulate the mapping of small and linear patches. In the simulation, the feature was represented by a high spatial resolution raster and was resampled to a low resolution raster representing the remote sensing raster grid in order to simulate its sub-pixel patch location. The remote sensing raster grid was represented by low resolution pixels whereby each pixel was made up of 101^2 high resolution pixels (sub-grid) (Figure 3.4).

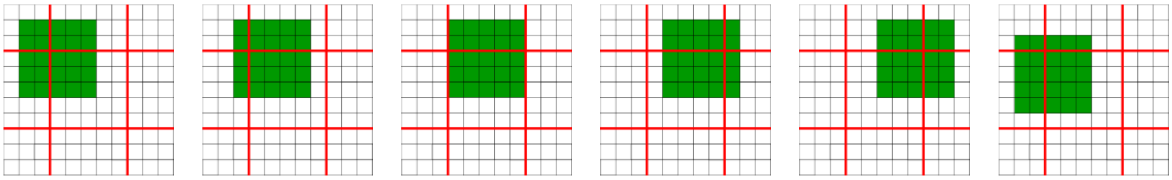


Figure 3.4 Simplified example of the simulation model. The remote sensing data is represented by a low spatial resolution grid (red lines) and the patch (solid green square) is represented by a high spatial resolution sub-grid (thin grey lines). For this example only 6 different positions of the patch are shown out of the 25 possible locations. The real model has a much higher spatial resolution than this example with 10,201 horizontal and vertical positions. Furthermore the patches are rotated at 5 different orientations.

Approximately 225 combinations of length to width ratios and areas were tested for 3 classification thresholds. We considered length to width ratios from 1 (square) to 10 (linear strip) with a step of 0.25 and areas ranging from 0 to 6 pixels and a step of 1. Furthermore, additional points were simulated for specific graphs or equations presented in the results where values outside this range were required or extra points were required for certain sections of some graphs to improve their visualisation. For each combination of length, width and area the computer simulation repeatedly systematically shifted the grid in 1/101 pixel steps vertically and horizontally with respect to the features location (Figure 3.4). As well as changes in the vertical and horizontal position of the feature we simulated different orientations of the feature. For each feature, the grid was shifted over 101 vertical and 101 horizontal positions thus testing a total of 10201 different grid positions per orientation.

In order to simulate different orientations the feature was rotated at 5 different angles from 0 to 45 degrees, thereby capturing all possible orientations with respect to the grid that affect classification. The 10201 iterations of different grid positions were repeated for each orientation resulting in a total of 51005 iterations for each feature.

The classification technique used to assign either patch (feature) or matrix (non-feature) was based on the proportion of area covered by a patch for each grid pixel. For the default classification (threshold of 0.5); if greater than 50% (i.e. the majority) of a pixel was covered by a patch the pixel would be classified as patch (e.g. Figure 3.2b-e). As well as the default majority rule, we tested 2 other binary classification thresholds to simulate the effect of detectability or local contrast (e.g. Figure 3.2f) by weighting the patch and surrounding matrix's contribution to the value of the pixel differently: 1) the patch must occupy more than 75% of the grid area in order to be classified as patch and 2) the patch needs to occupy more than 25% of the pixel area to be classified as patch.

For each grid position, accuracy and extraction probability was calculated by comparing the difference between the area classified as patch versus matrix in the grid and the sub grid (Figure 3.5). Differences in the area of each class were calculated using the high spatial resolution sub-grid. Accuracy was measured with errors of commission and omission as well as mapping accuracy which was calculated using equation 3.1. The accuracy measures were calculated for each position and then averaged over all the 51005 positions for each feature. Probability of extraction was calculated based on the proportion of 51005 position iterations in which any pixel was classified as patch, indicating that at least some part of the feature was detected. For a feature to be considered extracted only, a single grid pixel needed to be classified as patch. Thus a feature may be extracted but have a low accuracy.

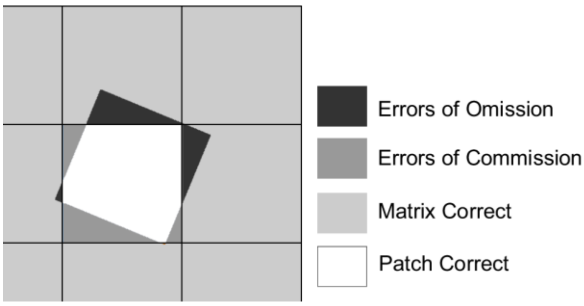


Figure 3.5 Example of error calculations for a single iteration out of 51005 performed for each feature.

Patch Mapping Accuracy = Area of $patch_{correct}$ / (Area of $patch_{correct}$ + Area of $patch_{omission}$ + Area of $patch_{commission}$).

Equation 3.1 Patch Mapping Accuracy

The final model tested: 225 combinations of length to width ratios x 3 classification thresholds x 5 orientations x 10201 grid positions.

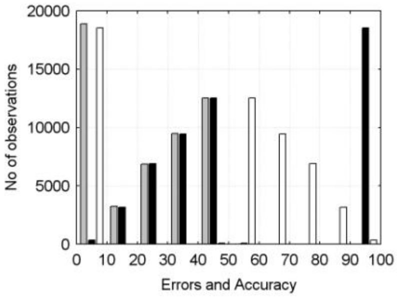
Using the simulation model described above this study investigated seven aspects of mapping small and linear patches, focusing on the effects of patch area, elongation and position on classification accuracy and extraction probability:

1. *Distribution of error and accuracy for all horizontal and vertical position combinations*
2. *Effect of area* on accuracy and extraction probability
3. *Effect of elongation* on accuracy and extraction probability
4. *Effect of elongation and area on errors of omission and commission.*
5. *Effect of feature orientation* on accuracy and extraction probability
6. *Effect of position* on accuracy and extraction probability
7. *Overview of effect of length and width ratio, area and classification threshold on accuracy and extraction probability*

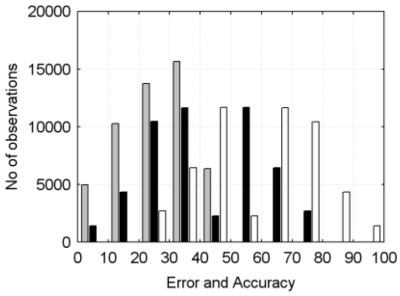
3.3 Results

3.3.1 Distribution of error and accuracy for all horizontal and vertical position combination

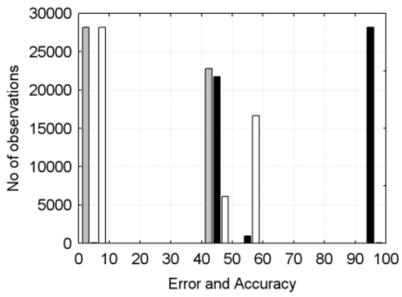
The response of patches to grid position is described using a histogram measuring error and accuracy for all x,y position combination (Figure 3.6). It was found that patches have a low probability of extraction when the feature is of a similar size to the grid, or is smaller than the grid. The histogram of error then contains many observations in the 0 and 100% categories for errors of commission and producer accuracy (Figure 3.6a). This occurred when the patch was not extracted at all and omission errors were 100%. When the patches were 1 pixel length × 1 pixel width (From here on patch length and widths are written with units omitted) or smaller, they were only represented by 1 or 0 pixels. However, larger features such as 2 × 1 patches (Figure 3.6b) and 2 × 2 patches (Figure 3.6d) were represented by 1 or more pixels. Each peak and trough in the histogram corresponds to a pixel that was classified as patch. For example when the patch was 2 × 1 there were two peaks in accuracy and omission associated with the fact that sometimes the patch was either represented by 1 or 2 pixels (Figure 3.6b).



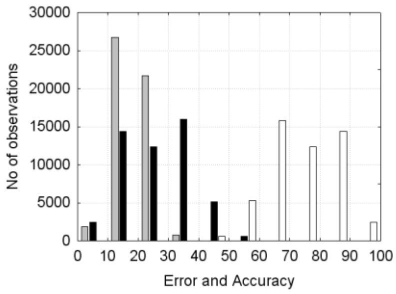
a) 1 x 1 pixel width, threshold: patch=0.5, Matrix= 0.5, Pr of Extraction = 0.64



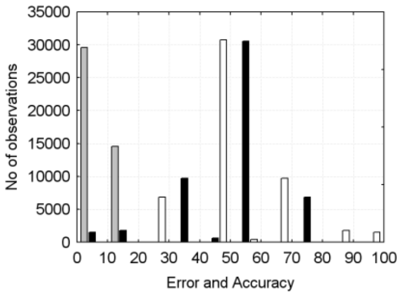
b) 2 x 1 pixel width, threshold: patch=0.5, Matrix= 0.5, Pr of Extraction = 1



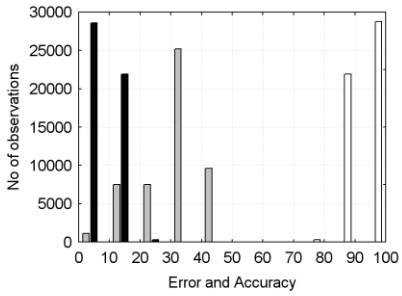
c) 2 x 0.5 pixel width, threshold: patch=0.5, Matrix= 0.5, Pr of Extraction = 0.45



d) 2 x 2 pixel width, threshold: patch= 0.5, Matrix= 0.5, Pr of Extraction = 1



e) 2 x 2 pixel width, threshold: patch=0.75, Matrix= 0.25, Pr of Extraction = 1



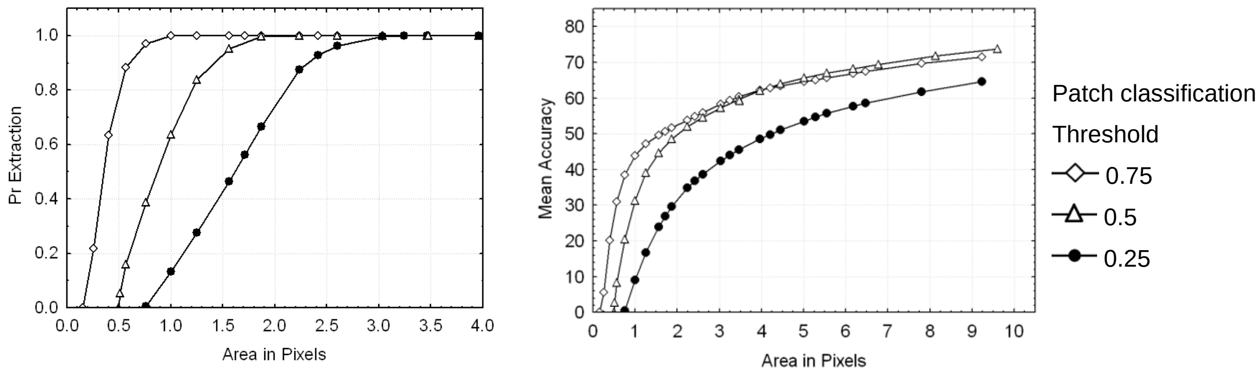
f) 2 x 2 pixel width, threshold: patch= 0.25, Matrix= 0.75, Pr of Extraction = 1

Figure 3.6 Histograms of commission, omission and accuracy for 4 different patch sizes and 3 different classification thresholds. Each histogram contains 51,005 grid positions observations, grouped into bin widths of 10 (e.g. *x*-axis scale is: 0–10, 10–20, 20–30 etc). a–c) Patch sizes of 1 × 1, 2 × 1 and 2 × 0.5 pixel lengths with patch and matrix weighted equally d–f) Patches of 2 × 2 with 3 different classification thresholds.

When the patch was 2 × 0.5 it was extracted 45% of the time, however, only as a single pixel, with approximately 50% of the patch classified correctly and a similar amount of commission errors (figure 3.6c). Once a patch was above a threshold size the probability of extraction was 1 and errors decrease (Figure 3.6d). If the classification threshold was weighted in favour of extracting patches (Figure 3.6e) there were greater errors of commission than omission as patch area was overestimated. Finally, if the classification threshold was weighted in favour of extracting the matrix there were greater errors of omission than commission (Figure 3.6f).

3.3.2 Effect of pixel area

Larger sized patches were always extracted regardless of classification threshold as the interior area to edge becomes greater. Once the area of a square was greater than 2 pixels the probability of extraction was 100% for 0.5 classification threshold (Figure 3.7a). For a classification threshold of 0.75 and 0.25 the area of a square feature needed to be at least 1 and 3 pixels respectively for a 100% probability of extraction.



a) b)

Figure 3.7 (a) Probability of extracting square patches vs. area for 3 classification thresholds. (b) Mean mapping accuracy of square patches vs. area for 3 classification thresholds.

As would be expected, with increasing patch size, the mean accuracy also increased (Figure 3.7b). For patches with an area between 0 and 2 pixels and a classification threshold of 0.5 the initial increase in accuracy was steep, up to around 2 pixels area. There was greater error for classification thresholds of 0.25, as errors of omission were always high due to the dominance of the surrounding matrix. Whilst for classification accuracy of 0.75, initially accuracies were higher than using the 0.5 classification threshold, however, after feature size reached 4 pixels there were greater inaccuracies. This was the result of errors of commission increasing overall inaccuracies due to the classification threshold weighted in favour of the patch. Thus for larger areas a classification threshold of 0.5 based on the majority rule had the highest accuracy. However, the greater the length to width ratio, the larger the feature area had to be in order for a classification threshold of 0.5 to result in a more accurate classification than for thresholds of 0.75. This was also related to the ratio of interior pixels to edge pixels.

The following equations were fitted using non-linear regression to two subsets of all the simulated data: (i) square patches with a classification threshold of 0.5 (corresponding to the curves in figure 3.7) and (ii) patches with a length to width ratio of 4 and a classification threshold of 0.5 (corresponding to the curve in figure 3.9d) (Equation 3.2). The equations were fitted in order to interpolate between the points calculated by the computer simulation. They approximate the relationship between probability of extraction and area; and mean accuracy and area, for both data subsets. For these subsets the simulation was run up to a maximum area of 280 pixels, thus the equation is not valid outside this range. Initially, we attempted to fit simple functions (e.g. exponential) but found them inadequate. We then fitted multiple more complex functions for both data subsets and chose which function best fit the points based on their curves R^2 values and a qualitative judgment of how well they interpolated between the points. We found no single function could be used for both datasets.

$$MeanAccuracySquare = \begin{Bmatrix} 0, -\infty < x < .5 \\ \dfrac{17057.3x}{0.001763 + x} + \dfrac{36.171x}{9.47 + x} - 16998.7,\ .5 \le x < \infty \end{Bmatrix}$$

$$MeanAccuracyL/W4 = \begin{Bmatrix} 0, -\infty < x < .5 \\ 84.999x^{0.023} - 68.929x^{-0.525},\ .5 \le x < \infty \end{Bmatrix}$$

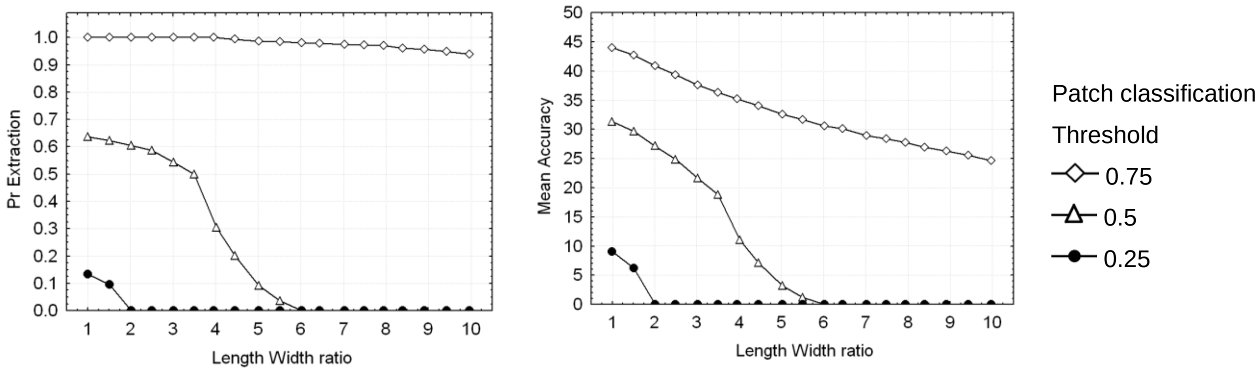
$$\Pr ExtractionSquare = \begin{Bmatrix} 0, -\infty < x < .5 \\ \dfrac{-0.765 + 1.59x}{1 - 0.17x + 0.439x^2},\ .5 \le x < \infty \\ 1, 1 \le x < \infty \end{Bmatrix}$$

$$\Pr ExtractionL/W4 = \begin{Bmatrix} 0, -\infty < x < .5 \\ -0.446 + \left(1.451 * \left(1 - \dfrac{x^{-3.33}}{0.876^{-3.33} + x^{-3.33}}\right)\right),\ .5 \le x < \infty \\ 1, 1 \le x < \infty \end{Bmatrix}$$

Equation 3.2 Curves fitted to the simulated data for square patches and linear patches with a length to width ratio of 4 for a classification threshold of 0.5. Valid for ranges of χ from 0 to 280, where χ is area in pixels.

3.3.3 Effect of elongation

The effect of increasing elongation was a decrease in the probability of extraction and mean accuracy (Figure 3.8). A patch of a single pixel in area has a probability of extraction of around 64% when it is a square, however, once the length to width ratio is greater than 6 it will no longer be extracted for 0.5 classification threshold. If the classification threshold favours patches the effect of elongation was less dominant, though it resulted in greater errors of commission.



a)

b)

Figure 3.8 (a) Probability of extracting patches of a single pixel in area vs. length width ratios. (b) Mean Patch accuracy of patches of a single pixel in area vs. length width ratios.

3.3.4 Effect of elongation and area on errors of omission and commission

Smaller and more elongated patches had larger errors of omission than commission (Figure 3.9 and Figure 3.10). However, as they became larger and more compact these errors balanced out, as misidentification occurs around the edge of patches. The interior pixels of a patch are always classified correctly as they are in the majority regardless of their position. For square features errors of commission were at their highest around 1.25 pixels and decreased with increasing area (Figure 3.9b). Errors of omission also decreased with increasing area as accuracy increased (figure 3.9c). A similar pattern could be seen with linear features (Figure 3.9d,e,f), except, the increase in accuracy with area was less steep.

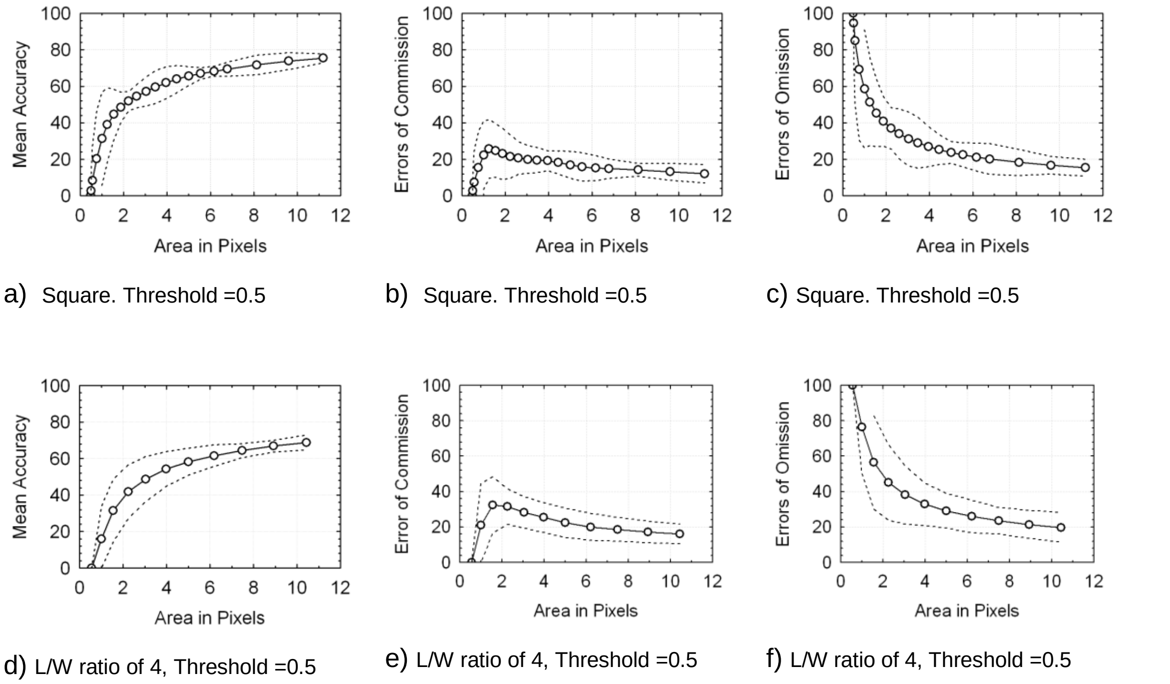


Figure 3.9 a) Mean mapping accuracy vs. area of square patches. b) Mean errors of Commission vs. area of square patches. c) Mean errors of omission vs. area of square patches. d) Mean mapping accuracy vs. linear patches with a length to width ratio of 4. e) Mean errors of commission vs. area of linear patches with a length to width ratio of 4. f) Mean errors of omission vs. area of linear patches with a length to width ratio of 4. The dotted lines represent +/− 1 standard deviation.

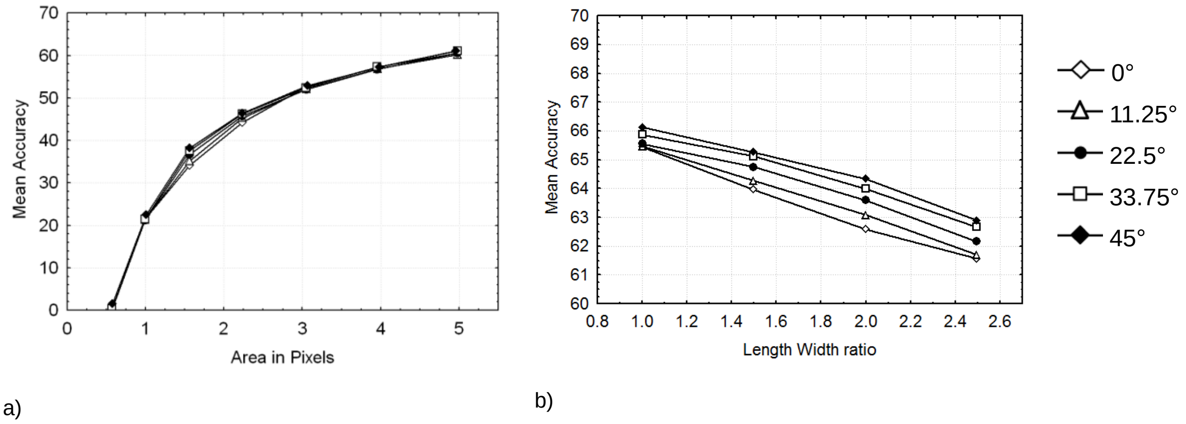


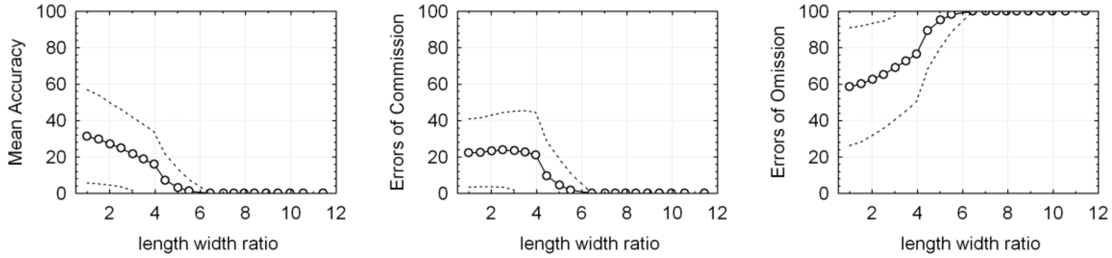
Figure 3.10 Mean patch accuracy vs. patch orientation. (a) Area of patches with a length to width ratio of 3 vs. mean accuracy. (b) Length to width ratios for a patch of 5 pixels in area vs. mean accuracy of square patches.

3.3.5 Effect of feature orientation

Orientation did not have a large effect on classification in comparison to the other effects. The probability of extraction was almost exactly the same regardless of the orientation. Changing orientation resulted in small differences in mean accuracy for patches of certain sizes (Figure 3.10a,b). This difference in mean accuracy was greater for more elongated patches (Figure 3.10b). For example there was a 1.5% difference in mean accuracy between patches orientated at 0° to 45° with a length to width ratio of 1.5 and area 5 pixels (Figure 3.10b). Mean accuracy was lower when patches had a similar orientation as the grid. Increasing elongation resulted in greater differences in mean accuracy between orientations. For patches of 5 pixels, with a length to width ratio of 6.5, the difference in mean accuracy was 2%, compared with 1% for square patches. However, small differences in accuracy of less than 1% were difficult to detect using the simulation due to resampling errors occurring when features were rotated.

3.3.6 Effect of position

The effect of the location of the grid can be described by the standard deviation of error (Figure 3.9 and Figure 3.11). A high standard deviation indicates that the position of the grid has a large effect on the outcome of classification making it difficult to predict the accuracy of classification for those features. Figure 3.9a,b,c shows that for square patches as the area approached 1 pixel the standard deviation of accuracy and error increased whereby it reached a maximum at 1 pixel area. The standard deviation of error and accuracy decreased after 1 pixel area as the feature became larger. As the area became smaller and the shape more elongated the standard deviation of accuracy and error was closer to 0, which was the result of features being rarely extracted (Figure 3.9 and Figure 3.11). Whilst, larger and more compact features had lower standard deviations indicating less of an effect of position on classification.



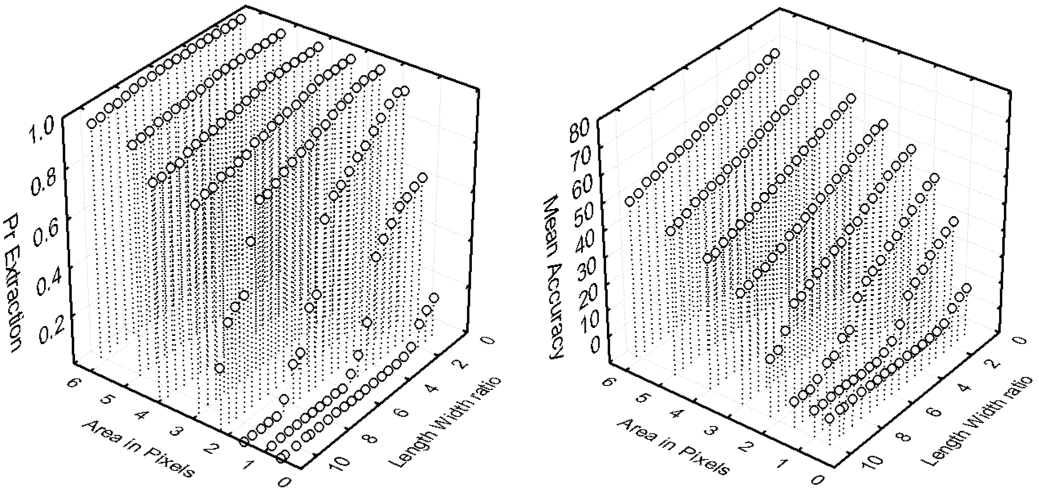
a) b) c)

Figure 3.11 a) Mean mapping accuracy vs. width to length ratios for a feature of 1 pixel in area. b) Errors of commission vs. width to length ratios for a feature of 1 pixel in area. c) Errors of omission of various sized of various length to width ratios for a feature of 1 pixel in area. The dotted lines represent +/− 1 standard deviation.

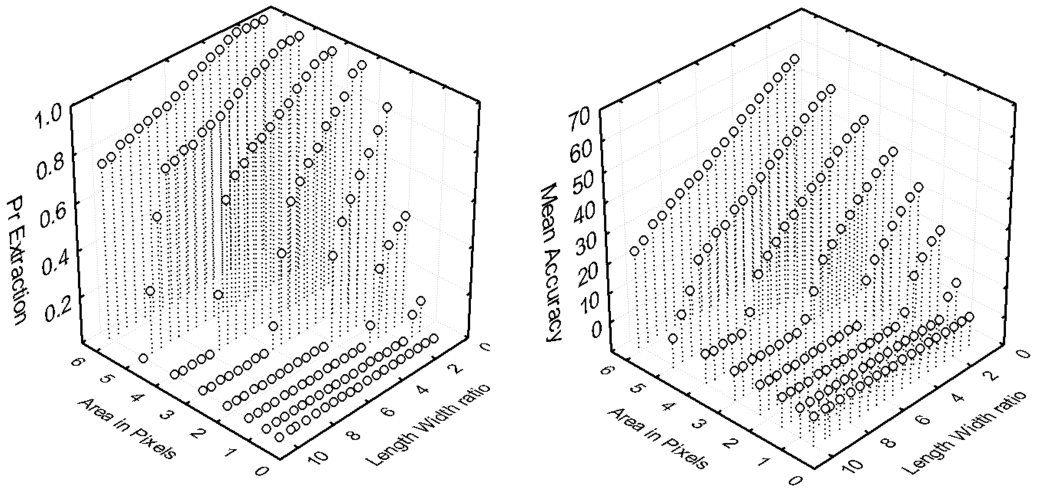
3.3.7 Overview of effect of length and width ratio, area and classification threshold on accuracy and extraction probability

Figure 3.12 shows the relationship between elongation and area and its effects on accuracy and probability of extraction for three different classification thresholds for all of the simulated data. Previously shown bi-plots (Figure 3.7-Figure 3.11) showed interesting subsets of the data in areas of rapid change in this relationship. Figure 3.12 demonstrates that depending on the size and elongation of a patch and the classification threshold, accuracy and probability of extraction will vary greatly. For example, for a classification threshold 0.5, a square with 2 pixel area has a mean accuracy of 50%. However, a rectangle with a width to length ratio of 4 has an area of 3.3 for the same mean accuracy. While a rectangle with a length to width ratio of 8 has an area of 5.4, also for the same accuracy. The relationship between area, elongation and classification will change with the classification threshold used. This change is more than a shift along the x and y axis but a change in the shape of the graphs in all dimensions for the 3 different classification thresholds shown in figure 3.12. Thus all factors, classification threshold, elongation and area can greatly affect accuracy and probability of extraction.

a) Classification threshold of 0.5



b) Classification threshold of 0.25



c) Classification threshold of 0.75

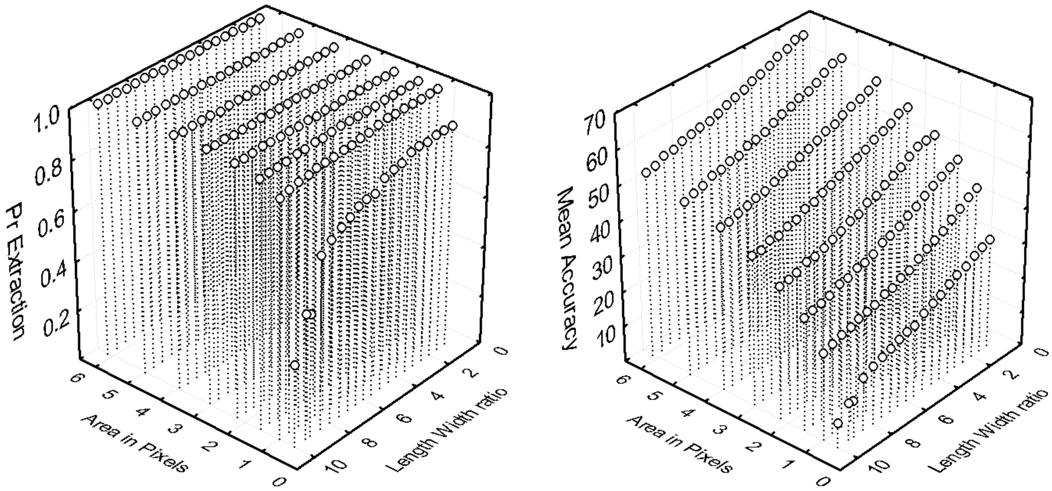


Figure 3.12 Probability of extraction versus length to width ratio and area for classification and mean accuracy versus length width ratio and area. For classification thresholds: 0.5 (a), 0.25 (b) and 0.75 (c).

3.4 Discussion

This study described statistically what many ecologists, mapping professionals and remote sensing users intuitively understand; that linear and small features are more difficult to accurately classify than compact and large features. It expanded on studies by Congalton (1997) and Wehde (1982) which investigated some components of this phenomenon, using simple datasets with limited numbers of shapes and sizes. Our study has made estimates using area and dimensions and described their corresponding probability of extraction, mean classification accuracy and standard deviation based on sub-pixel patch location. Whist the majority of previous studies have used a single figure such as area in pixels to describe the minimum size of feature that could be extracted. We demonstrated that estimations of minimum feature size need to include feature dimensions as well as the area. Width or area alone is not enough. For example, take two features extracted with the same 75% mean classification accuracy, (1) a rectangular feature with a length to width ratio of 4 and (2) a square. The width (shortest side) would be 1.8 and 3.3 and their areas 12.3 and 11.0 pixels respectively (Table 3.1), for a classification threshold of 0.5. Estimates by previous studies of the smallest discernable feature vary from the equivalent of > 1 to 4 pixels (Cracknell 1998; Hengl 2006). The work of these authors is in agreement with our results in predicting possible feature extraction. However, we found that in order to extract patches consistently and accurately features must be many times larger than spatial resolution. Our results suggest that extracting features with pixel areas based on estimates made by these studies would have a low accuracy and high variability in accuracy.

Table 3.1 Minimum patch sizes required to achieve an extraction probability and accuracy of 75% for square and linear features (length to width ratio of 4) for various sensors estimated by the simulation model.

		Square with Pr Extraction of 75%	Square with mean Accuracy of 75%	Linear Feature (LW ratio=4) with Pr Extraction of 75%		Linear Feature (LW ratio=4) with mean Accuracy of 75%	
Area (Pixels)		1.1	11.0	1.2		12.3	
Dimensions (Pixels)		1.0 x 1.0	3.3 x 3.3	.5 x 2.2		1.8 x 7.0	
Sensor	**Sensor Res. (m)**	**Width (m)**	**Width (m)**	**Width (m)**	**Length (m)**	**Width (m)**	**Length (m)**
Pixels	-	1.0	3.3	0.5	2.2	1.8	7.0
Aerial camera (Flying height dependent – indicative only)	0.2	0.2	0.6	0.1	0.4	0.4	1.4
Quickbird-2	2.4	2.5	8.0	1.3	5.3	4.2	16.8
Ikonos-2	4.0	4.2	13.3	2.2	8.8	7.0	28.1
SPOT XS	10.0	10.5	33.2	5.5	21.9	17.5	70.1
LANDSAT 7 ETM+	30.0	31.5	99.5	16.4	65.7	52.6	210.4

The effect of grid position, feature area and dimensions had a greater effect on classification when the feature's scale approached the grid scale either through elongation of the feature or by having a similar area. Extraction probability and mean accuracy decreased and the standard deviation of accuracy increased when feature resolution approached grid resolution. A classification threshold weighted in favour of the patch (0.75) negatively affected classification accuracy when feature area became large. However, when grid and feature resolution were similar, mean accuracies were higher for this classification threshold than when it was based on the majority rule (0.5). The position effect was also more pronounced when feature resolution and grid resolution were similar, resulting in greater variability in accuracy. This indicates that in order to capture linear or small features consistently with any degree of accuracy the grid should be many times finer than the size of the feature. For example, a square patch with an 11 pixel area had a mean accuracy of only 75% (+/− 2.4 STDV). The findings of this study validate Strahler et al. (1986)'s assertion that objects need to be several times smaller or larger than the spatial resolution in order to regard the scene model as either H or L resolution.

We found that lower spatial resolution resulted in reduced classification accuracy. However, research using semi-variograms in order to find the optimum spatial resolution (e.g. Atkinson and Curran 1997; Hyppanen 1996; Marceau et al. 1994) show that degrading the spatial resolution may result in higher classification accuracy (Townshend and Justice 1988). These studies however, ignored the effects of degrading spatial resolution on the extraction of small features. As images are degraded the level of fragmentation will decrease with smaller patches disappearing first (Lechner et al. 2008). The decreased classification accuracy at fine scales can be the result of increases of within class spectral variability due to oversampling (Aplin 2006). For example, if the feature of interest is a forest stand, as the spatial resolution increases the gaps between individual trees containing understory elements increase and thus may be misidentified. Although Cushnie (1987) found that this was dependent on the land cover class, as some classes can be homogenous and internally consistent and thus there would be no decrease in overall classification accuracy at higher resolutions. Therefore the findings of this study will be more relevant to the extraction of features that are homogenous such as tree stands with dense canopies, hedgerows, sandy beaches and roads.

The variability in classification resulting from the effect of grid location is an important consideration, as within the same map, features of the same spatial and spectral characteristics may be detected in one instance and not in another. If map users consider these small features important such as for the mapping of connectivity and wildlife corridors, an understanding of the random nature of the probability of a feature being extracted and the variability in accuracy within a scene needs to be understood. For example, land managers may use a thematic map to determine the probability of wildlife migrating between three large reserves within an urban landscape using roadside vegetation as corridors. The probability of migration between reserves may be determined by the presence of linear vegetation connecting the reserves. However, if linear vegetation is of a similar width to grid width it may be distinguished in some cases and not in others, even though it may have exactly the same dimensions. Thus the map may give the appearance that a wildlife corridor exists between two patches and doesn’t exist between another two patches even though in reality it exists but was not extracted.

This study can guide map users as to the appropriate spatial resolution needed for their research. Most users will have a general idea of the dimensions of the features that exist within the landscape and therefore can then make assumptions as to the appropriate resolution required to extract the features in their study area. There is not a single solution for all users. For example, in some connectivity studies ensuring that a portion of a linear strip is extracted is good enough for their purposes. Other users may require that all linear strips be extracted with a 95% accuracy and thus would require a much higher spatial resolution. Table 3.1 describes some practical applications of the simulation modelling in order to estimate the required resolution for various aerial and satellite sensors to extract and accurately classify square and linear features (length to width ratio of 4). Equation 3.2 can also provide rough estimates to predict accuracy and extraction probability for these features. As a general rule of thumb we would suggest that the spatial resolution of the grid should be many times higher than the scale of the feature in order to accurately extract these features e.g. Table 3.1 shows that in order to extract a square shaped feature with a mean accuracy of 75% (+/− 2.4 STDV) the feature needs to be 3.3 × 3.3.

Map users can use the findings of this study to estimate the probability of a map identifying linear vegetation of interest correctly independently of the error matrix. Conventional maps use the classification error matrix (Congalton 1988) to express errors of commission and omission for each class. However the error matrix does not take into account the spatial distribution and variation in mapping errors (Steele et al. 1998). Localized or point specific error is not documented. Large scale studies often assume that errors of commission are balanced with errors of omission (Cunningham 2006). However this is not always the case, as smaller patches had larger errors of omission than commission as they are often surrounded by more dominant classes. In cases where a feature is found at the intersection of several features it is likely to disappear as it will be in the minority amongst those intersecting pixels. Thus land cover classes found in linear or small patches will be under-represented in the landscape. These patches have small areas in comparison with contiguous vegetation remnants, thus they could easily be misclassified without influencing the calculation of accuracy in an error matrix. This can result in an image that may appear highly erroneous with respect to pattern, but has a good classification based on area classified correctly.

The use of a simulation study has allowed for the isolation of a grid location, feature size and elongation phenomena in order to test the scope of their effect on classification. The results of the study represent the best case scenario for remote sensing where the accuracy of classification is only affected by the shortcoming of the raster grid's geometric properties. However, when using real images other issues can further reduce classification accuracy. There are many processes in the creation of a land cover dataset; from selecting the remote sensing device to post-processing, and accuracy assessment (Lu and Weng 2007) which all potentially affect classification. This is especially true for processing and sensor characteristics that resample and/or result in a smoothed image such as the application of filters, resampling for geo-rectification and the effect of the sensors point spread function. Lechner et al. (2008) demonstrated that smoothing an image will result in fine scaled features such as small and linear patches being lost.

In order to overcome the limitations of the traditional hard classification scheme many other land cover classification techniques have been developed such as fuzzy classification or soft classification, super resolution imagery and linear feature extraction techniques. Fuzzy classification models of vegetation quantify the degree of membership to each class for each pixel (Foody 1996). This method allows for the identification of objects that may be smaller than the pixel size, however there exist many difficulties in accurately identifying these objects, assessing their accuracy and using them within models (Lu and Weng 2007; Tatem et al. 2002). An alternative method is to increase the spatial resolution of imagery that is too low to meet requirements. There is no generally accepted method for this (Aplin 2006), and different techniques have produced varying results. Thornton et al.'s (2006) super-resolution mapping method was found to work well for objects approximately as wide as a pixel, however, objects of half a pixel width had low classification accuracy. Whilst Tatem's (2002) super-resolution technique recreated sub-pixel spatial pattern class proportions but did not map the true location of sub-pixel features. Other methods which focus on extracting linear features are predominately being used to extract roads to update GIS databases from imagery (Quackenbush 2004) rather than linear vegetation where correctly classifying their size and shape is equally as important. Additionally, linear feature extraction techniques ignore other non-linear features thus having limited application.

Super-resolution imagery, fuzzy classification, linear feature extraction and ecological models developed to cope with new spatial data models are likely to overcome some of the negative effects of the phenomena discussed in this paper in the future. However, currently the majority of classification approaches used are based on the hard classification paradigm (Lu and Weng 2007). Whilst methods such as super-resolution mapping and the use of soft classification can be used to deal with the grid position and patch position effects, data users may not always be data producers thus an understanding of the limitation of their data will always be a requirement. Furthermore, soft classification methods are not always appropriate data input for some applications, such as in landscape ecology where models have been built around the traditional hard classification system such as meta-population models. The traditional hard classification approach is still the most popular due to its simplicity even with all its limitations. Some of the most important continent wide datasets are hard classifications such as the European LU/LC dataset Corine, and USA's NUCL.

3.5 Conclusion

This study highlights several issues that exist in using the pixel model to describe geographic phenomena. It focuses on understanding misclassification resulting from patch size approaching the scale of the sensor's spatial resolution. We found that small and/or elongated patches have a reduced probability of extraction, a reduced mapping accuracy and an increased variability in accuracy due to the effects of grid position. To extract those patches accurately, the grid spatial resolution should be many times finer. For example, for square patches with a mean classification accuracy of 75%, the grid pixel area has to be 11 times smaller than the patch size. This relationship between patch size and shape and classification was also affected by patch detectability. For similar grid resolution and patch size, mean accuracies were higher if the classification threshold was weighted in favour of detecting patches. Such weighting, however, negatively affected classification accuracy for large patch sizes. For those patches, a classification based on the majority rule (0.5) had the highest classification accuracy.

Our research suggests that within the same scene, classification error for patches of a size similar to the grid resolution may differ, and in some cases not be extracted at all, because of the random location of the grid. Furthermore, error within a land cover class is likely to be disproportionately higher for small and linear patches. High classification errors in small and linear patches, however, may not influence the error reported by confusion matrices because of the proportionally small patch sizes. In landscape ecology, accurately characterising the spatial arrangement of landcover classes by means of the extraction and accurate classification of small and linear patches can be more important than estimating correctly the total area of a landcover class. Future research using real data and building on our findings may focus on developing error reporting methods to describe the uneven spatial distribution of errors across the scene and its impact on the characterization of landscape pattern.

Chapter 4 A study on the impact of Scale Dependent Factors on the Classification of Landcover maps

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4.1 Introduction

4.1.1 Scale Dependent factors

Scale dependent factors such as pixel size, study extent and the application of smoothing filters affect the classification of landcover. These factors are dependent on the remote sensing data, classification techniques and class description used. Landcover maps will vary in their extent, patchiness and accuracy of classified areas based on the relationships between these factors. Many studies have investigated these factors using empirical data and have come to conclusions based on unique case studies investigating one factor in isolation (Huang et al. 2006). This study holistically investigates the impact different scale dependent factors had on the classification of landcover maps to better understand their interactions and their relative importance.

In many studies, data is collected at the most appropriate scale, however, for studies using remote sensing data, users are often limited to specific scales available. The most appropriate scale for a study is a function of the environment (its spatial arrangement), the kind of information that is to be derived, and the classification technique used (Woodcock and Strahler 1987). Numerous combinations of these factors are possible and their effects are usually interrelated and scale dependent.

At different spatial scales, landscape composition and configuration will change. Area and spatial pattern will change when spatial dependent factors such as grain and/or extents are altered (Wiens 1989). Unfortunately, knowledge of how these spatial patterns change is limited (Wu et al. 2002).

The primary aim of this project is to investigate the relationship between scale dependent factors and landscape pattern, as measured by total area and landscape metrics in the context of vegetation extent mapping. The project is not aimed at solving the problem of uncertainty in spatial dependent factors, but rather is attempting to quantify its nature. While the development of an integrated model is not new to the field of remote sensing (e.g. Huang et al. 2006; Ju et al. 2005), many previous studies have investigated scale dependent factors, and reached conclusions based on site specific evidence, without considering the interactions between these various factors (Huang et al. 2006). This paper aims to provide greater understanding of how they interact and to examine their relative importance. Interactions between scale dependent factors were investigated from the users' perspective through examining a number of landscape metrics. These metrics were chosen because they are simple and they summarise important patch characteristics. They have straightforward practical uses such as the measurement of total area and mean distance between patches rather than purely characterising fragmentation such as the fractal dimension index.

This study is novel in that it uses real landscapes with a large study area and sample size. The majority of previous studies have either used simulated landscapes (e.g. Li et al. 2005) or real landscapes with small study areas and sample size (De Clercq et al. 2006; Wu et al. 2002).

4.1.2 Landcover maps

This study utilizes the Tree25 presence / absence tree cover data set produced for the Department of Sustainability and Environment's Corporate Geospatial Data library (DSE 2006) (Figure 4.1). This dataset is typical of woody / non-woody vegetation data layers used worldwide in land use planning and habitat mapping.

While the uses of this dataset are varied, its initial purpose was to provide a comprehensive and consistent dataset for tree cover monitoring for the state of Victoria (Australia). Furthermore it is expected to provide an excellent source of data for applications that require the identification of remnant tree cover such as connectivity analysis and habitat modelling (DSE 2006).

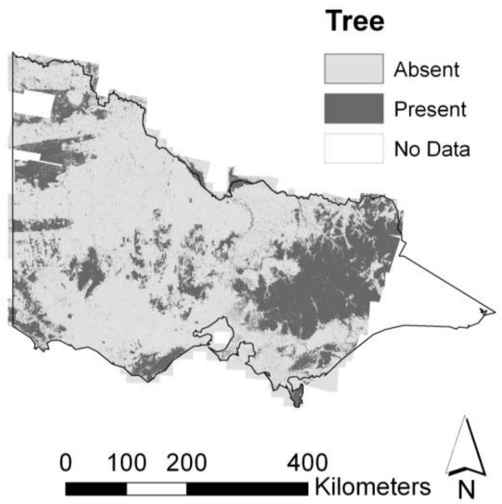


Figure 4.1 Map of the study area and Tree25, tree presence / absence data set overlaid.

4.1.3 Changing Scale Dependent factors

Pixel size (or spatial resolution) and extent were manipulated and a smoothing filter was used to examine the differences in classification. All variables were manipulated to simulate a range of conditions and determine how patchiness and patch area changed accordingly.

Pixel size is an important variable to investigate as using the default pixel size (i.e. sensor resolution) will result in a view of the world that relates to the sensor but may not necessarily reflect the needs of the question being asked (Fassnacht et al. 2006). Pixel size is one of the most important elements determining how other scaling factors will change. Pixel size controls the limit of the smallest feature which can be extracted from an image. For areas where vegetation is highly fragmented such as urban areas and where patches appear as small as median strips and backyards, Jensen and Cowen (1999) concluded that at least 0.5 to 10m spatial resolution is required. Resolution was altered to simulate differing sensor resolutions by degrading the original classified image.

The second factor investigated was the use of a smoothing filter. Pixel based landscape classification can result in a salt and pepper effect because spatial autocorrelation is not incorporated in the classification technique (Ivits and Koch 2002). A common practice used in remote sensing is smoothing the image by aggregating pixels to reduce classification error caused by this effect. The use of a smoothing filter will often result in the removal of edge complexity as well as increasing the minimum mappable unit (MMU). The MMU tends to be larger than the pixel size so that spatial and/or content information may be lost (Fassnacht et al. 2006). Larger MMUs may result in patches of interest being falsely combined within adjacent patches (Fassnacht et al. 2006). For this study the smoothing algorithm used was a majority filter. However, other filters can be used for the similar purposes such as mean or low pass filters.

The final variable investigated was extent, which is the total physical area covered by the data source. As the extent increases so does the probability of sampling rare classes (Wiens 1989). Furthermore, if grain size is fixed, fragmentation increases with increasing extent (Riitters et al. 2000). The effect of extent was investigated by comparing many landscape samples at different extents.

Landscape metrics were used to analyse the effects on landcover classification of varying pixel sizes, applying smoothing filters and changing extents. These metrics were chosen because they describe simple patch characteristics that users of the Tree25 data layer in Victoria often utilise. Users of landcover maps need a practical understanding of how scale dependent factors affect classification. For example, in the region of Victoria it is important to measure correctly the area of native vegetation, as a permit is required to remove, destroy or modify native vegetation from a landholding greater than 0.4 hectares (Cripps et al. 1999). Understanding the landscape metric ‘mean patch area’ is therefore critical when assessing the suitability of a particular landcover map for this purpose. Another example is to understand how the mean distance between patches changes as a result of altering scale dependent factors. An understanding of distance between patches is useful for population modellers to calculate the probability of dispersal between populations based on this distance (e.g. RAMAS (Akcakaya 2002)).

4.1.4 Data

The study area encompasses most of the state of Victoria which is approximately 227,416 km^2. The study area is dominated by broad acre cropping and crop pasture, vegetation and dryland pasture (Figure 4.2). There are a variety of abiotic and biotic processes occurring at multiple scales, resulting in a complex landscape composition and configuration.

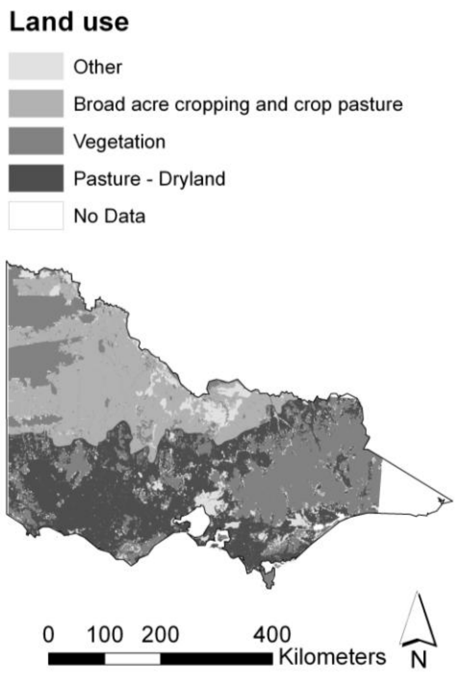


Figure 4.2 Map of land use in the study area.

Comparison of the effects of scale between landscapes as well as within landscapes is important as the relationship between spatial patterns and scale may not be linear. Each landscape will vary with respect to the different processes operating at various scales (Wu et al. 2002). For example, disturbance can operate at many different scales from housing development to large fires to tree falls. Simulating landscapes at different scales that concurrently reflect reality is likely to be very difficult.

Numerous studies have investigated scaling effects, but most of these studies have been confined to a few metrics or cover a narrow range of scales (Wu et al. 2002). Studies that have a large sample size tend to use simulated landscapes (e.g. Li et al. 2005). Real landscapes are used within this study, as opposed to computer generated simulated landscapes, such as the those created by software programmes, such as Rule (Gardner 1999) and SimMap (Saura and Mart´ýnez-Millán 2000). While simulated landscapes are a useful tool in terms of overcoming the impracticalities of replicating landscape scales, commentators such as Li et al. (2005) have suggested that simulated landscape models are insufficient in their ability to capture in detail the characteristics of real landscapes. This study is unusual in that the large study area allows for multiple replications at the landscape level of real landscapes.

4.2 Method

4.2.1 Data

The original classified data were derived from SPOT panchromatic imagery with a 10 metre pixel size through a combination of automated segmentation and manual classification (DSE 2006). No smoothing or filtering was applied at this layer creation stage. Tree cover is defined by the producers of the original dataset as woody vegetation over 2 metres with crown cover greater than 10 percent.

4.2.2 Post - Processing

The original data were post-processesed to test the effect of resolution, extents and applying a smoothing filter on classification. All processing was performed using ArcGIS 9.1. The original image was first degraded to different pixel sizes. A filter was applied to the degraded images to smooth the image. Finally, each combination of filtered and degraded images were clipped to different extents.

4.2.3 Pixel Size

Pixel size was changed by degrading the original image from 10 to 100 metres at 10 metre increments. In this paper a decrease in resolution is analogous to an increase in pixel size and vice versa.

4.2.4 Smoothing filter

A majority filter was used to smooth the image. The majority filter replaces cells in a raster based on the majority of their contiguous neighbouring cells. The majority filter process has two criteria to fulfil before a replacement occurs. The number of neighbouring cells of a similar value must be in a majority and these cells must be contiguous around the centre of the filter kernel (ESRI 2007a). A 3 x 3 kernel was used for this process. A majority filter is useful for post processing as it works with discrete data.

4.2.5 Extents

Subsets of this image were randomly clipped at 3000m, 10000m, and 20000m replicating landscapes of different extents (Figure 4.3). The extents represent the distance of a single side of a square. The image was clipped so that each replicate did not overlap. 20 samples were taken for each combination of smoothed image, extents and resolution with a total sample size of 600.

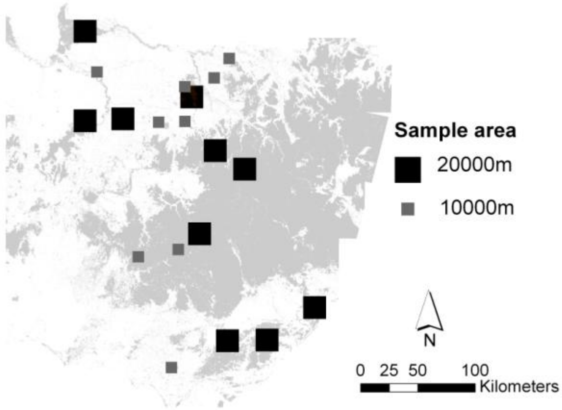


Figure 4.3 Clipped areas for western portion (50% of total area) of study area for extents 10000m and 20000m.

The lower bounds of the sampling size was set at 3 kilometres as suggested by Forman and Godron (1986), although it is recognized that in principle landscape size is related to the scale at which an organism perceives their environment. The upper limit was based on the approximate area of a small catchment, at around 20 kilometres. Furthermore, as the extents were increased beyond this amount, computer processing time increased markedly.

4.2.6 Calculating Landscape Metrics

Area was calculated based on pixels classified as either tree present or absent as identified by ArcGIS. Landscape metrics were then calculated using the Fragstats package (McGarigal et al. 2002). Five landscape metrics were used: patch number, mean patch area, mean patch density, mean nearest neighbour distance, and mean perimeter to area ratio.

4.3 Results

The total classified area remained relatively constant when the image spatial resolution changed. However, large differences in the patchiness of the image occurred as a result of altering the resolution and applying a smoothing filter. As image spatial resolution decreased (i.e. pixel size increased) or the smoothing filter was applied the subtle levels of patchiness declined. Small patches either aggregated into larger patches or completely disappeared (Figure 4.4). While most measures of patchiness appeared to be non-random in relation to the spatial dependent factors, this was not uniformly the case. For most metrics used it was impossible to test the effects of changing extent due to the low sample size and high variability.

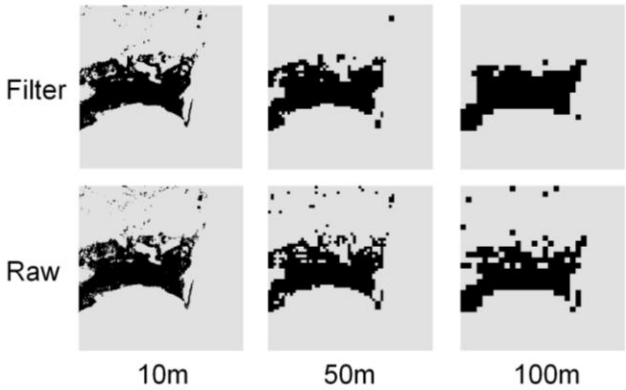


Figure 4.4 Example of processing. The original (raw) image at 10 metre spatial resolution was degraded up to 100 metres. For each degraded image a majority filter was used to smooth the image.

4.3.1 Mean number of Patches

It was found that the greater the extent, the greater the mean number of patches, and the lower the spatial resolution, the lower the number of patches identified (Figure 4.5). Additionally, using the smoothing filter also resulted in a lower number of patches.

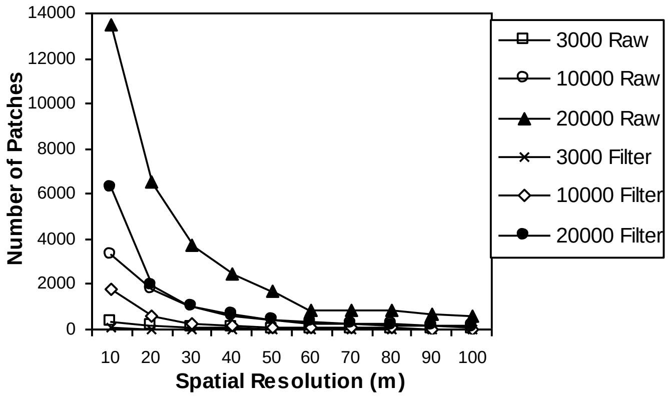


Figure 4.5 Comparison of the effect of changing extents (3000m,10000m, and 20000m), spatial resolution and applying a smoothing filter on the mean number of patches (Raw and Filter). For each combination of extent and application of smoothing filter n=20.

4.3.2 Mean Patch Area

The relationship between mean patch area and the spatially dependent factors was the opposite to mean number of patches. Decreasing the spatial resolution and the application of the smoothing filter resulted in an increase in mean patch area (Figure 4.5a). The mean number of patches changed as a result of changing the spatial resolution, however the total area classified as tree or non-tree remained constant (Figure 4.6b). Due to the high standard error resulting from the small sample size (n = 20) a comparison between extents could not be conducted. The differences between the value of proportion classified as present or absent for different extents is the result of high variability in the landscape. However, the filtered data tended to have a significantly ($P < 0.05$) lower proportion of cells classified as present for both 3000m and 20000m extents.

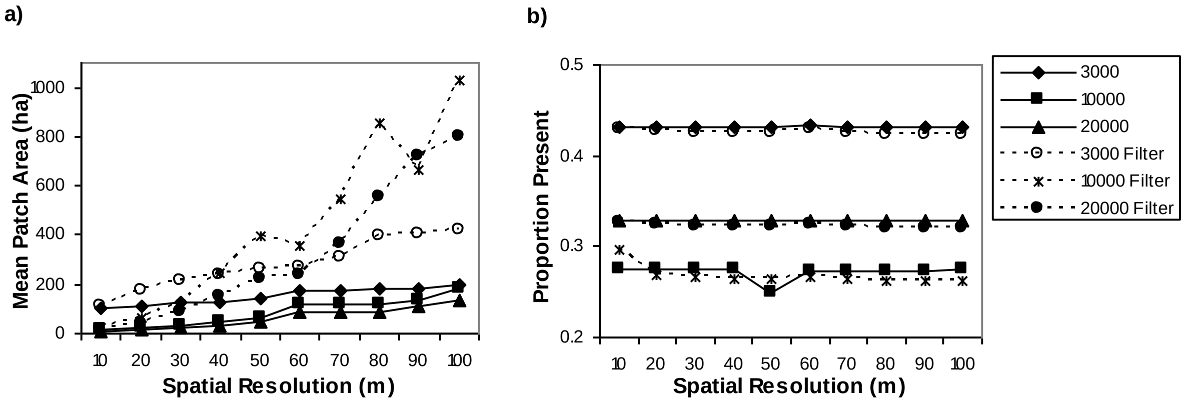


Figure 4.6 a) Spatial resolution versus mean patch area for 3 extent (3000m,10000m, and 20000m), and raw and smoothed data (Raw and Filter). b) Spatial resolution versus proportion of vegetation present for 3 extent (3000m,10000m, and 20000m), and raw and smoothed data (Raw and Filter). For each combination of extent and application of smoothing filter n=20.

The relationship between patch area and spatial resolution was not perfectly linear. The overall trend was to increase the mean patch area with decreasing spatial resolution and the application of the smoothing filter (Figure 4.6a). However, applying the majority filter at lower spatial resolutions resulted in a greater increase in the mean patch area than at higher spatial resolutions. For 3000m extents there was an increase in the mean patch area of 5% at 10m spatial resolution compared to 115% at 100m spatial resolution. For 20000m extents there was an increase in the mean patch area of 93% at 10m spatial resolution compared to 505% at 100m spatial resolution.

4.3.3 Mean Patch Density

Patch density was calculated as the number of patches in the landscape divided by the total landscape area. As the spatial resolution decreased the mean patch density decreased for all extents (Figure 4.7). This decrease was quite dramatic. At 10m spatial resolution there was a decrease in the mean patch density from 38.4 to 1.6 at 100m resolution, for 3000m extents and from 33.7 to 1.4 for 20000m extents. The results of applying a filter had a similar affect as decreasing resolution, i.e. decreasing mean patch density. However, applying the filter resulted in a greater decrease at lower spatial resolutions. For 3000m extents at 10m spatial resolution there was a decrease in the mean patch density of 53% compared to 71% at 100m spatial resolution. For 20000m extents at 10m spatial resolution there was a decrease in the mean patch density of 53% compared to 78% at 100m spatial resolution. Figure 4.8 shows the relationship between patch density and resolution for single samples compared to figure 4.7 which shows the mean of all the samples. Figure 4.8 also shows that as spatial resolution decreases patch density will predictably decrease. The relationship appears to fit an inverse exponential function.

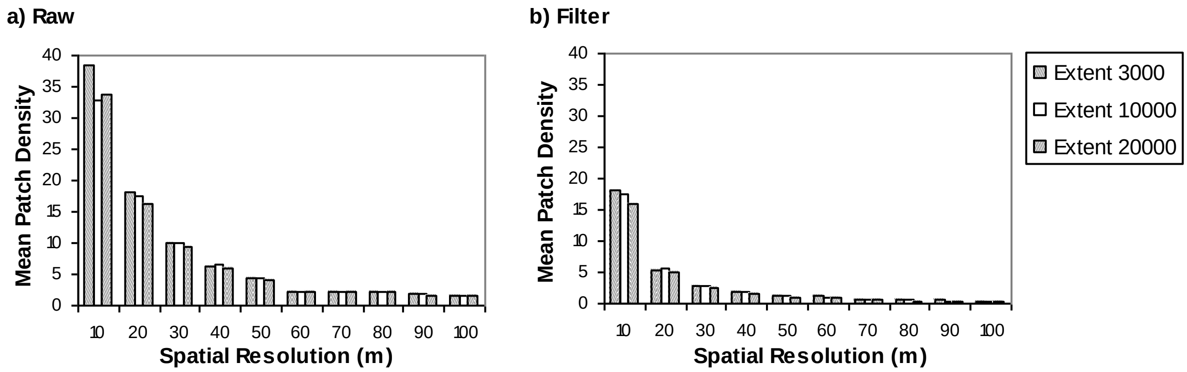


Figure 4.7 Spatial resolution versus mean patch density (number of patches in the landscape, divided by total landscape area) for 3 extents (3000m,10000m, and 20000m). For each extent n=20. a) Raw data. b) Data smoothed with a majority filter.

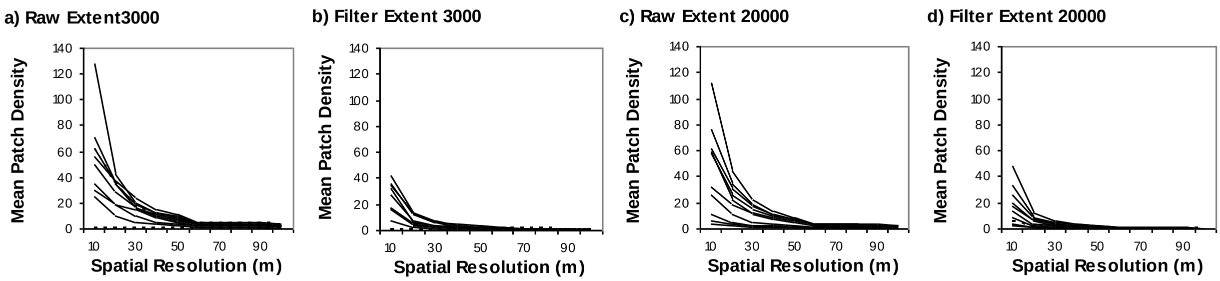


Figure 4.8 Mean patch density (number of patches in the landscape, divided by total landscape) for 10 samples at extents 3000m and 20000m for data before and after being smoothed with a majority filter.

4.3.4 Isolation and proximity

Isolation and proximity were calculated using the nearest neighbourhood value based on the shortest edge-to-edge distance for a patch of the same type. As spatial resolution increased the nearest neighbour distance generally increased (Figure 4.9). However, of all the measures of patchiness this appeared to be the least predictable. The variability appeared to be inconsistent and unrelated to spatial resolution. Furthermore, there appears to be no relationship between spatial resolution and using a smoothing filter (Figure 4.10).

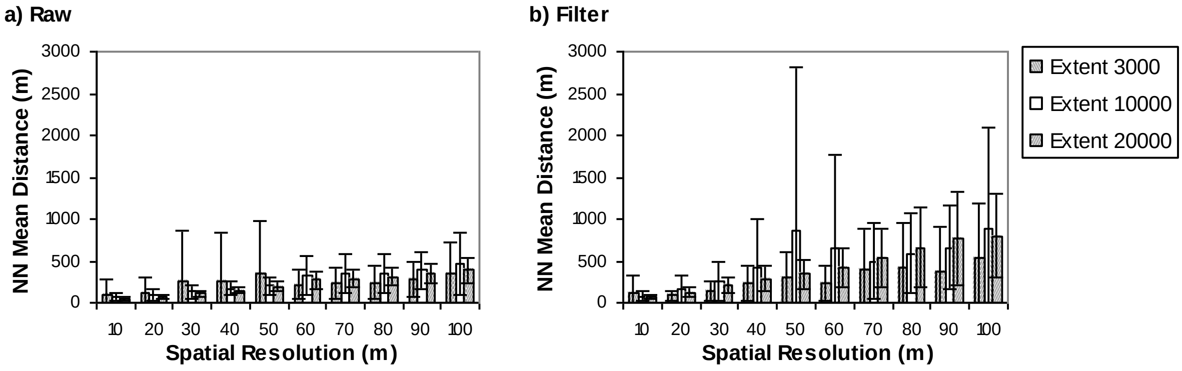


Figure 4.9 Spatial resolution versus mean euclidian nearest neighbour distance (m) for 3 extents (3000m,10000m, and 20000m). For each extent n=20. Error bars indicate standard deviation. a) Raw data b) Data smoothed with a majority filter.

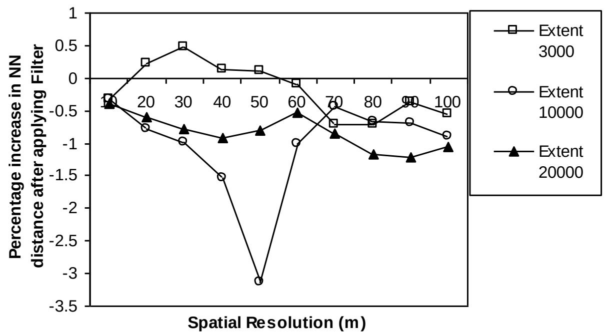


Figure 4.10 Spatial resolution versus percentage change in mean nearest neighbour distance between patches after applying the majority filter for 3 extents (3000m,10000m, and 20000m). For each extent n=20.

4.3.5 Perimeter to Area Ratio

Perimeter to area ratio describes the relationship between shape and area. As spatial resolution increased, the ratio decreased (Figure 4.11). The mean perimeter to area ratio and spatial resolution is the inverse of patch area. By default, the mean perimeter to area ratio is strongly related to patch area. For example, if shape is held constant and patch size increased there will be a decrease in the ratio. Applying the smoothing filter resulted in a predictable decrease in the mean perimeter to area ratio.

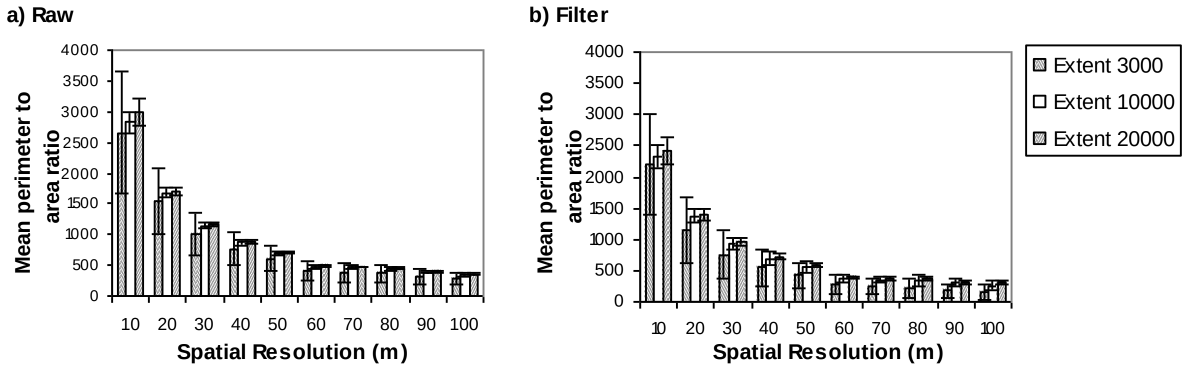


Figure 4.11 Spatial resolution versus mean perimeter to area ratio for 3 extents (3000m,10000m, and 20000m). For each extent n=20. Error bars indicate standard deviation. a) Raw data b) Data smoothed with a majority filter.

4.4 Discussion

This study clearly demonstrates that changes in scale dependent factors affect the patchiness and total area of landcover maps classified. While this study indicates that some relationships between factors were predictable, this was not always the case and not all metrics varied in the same way.

The effects of applying the smoothing filter are of particular interest. Applying the smoothing filter caused a greater increase in the mean patch area and greater decrease in the mean patch density at lower spatial resolutions. Furthermore, after applying the smoothing filter, significantly less area was classified as 'tree present' at all extents and spatial resolutions compared to when the filter was not applied.

Due to the small sample size and large variability it was impractical to compare the effects of changing the study area extents. We would expect greater variability in smaller extents and that a larger extent will have a greater probability of containing all the variability within a landscape. Furthermore, if the sample size was increased the mean of these samples should reflect the mean of the variability in the landscape. However, increasing the sample size or the sample area could be problematic as the area of real landscapes is finite.

4.5 Conclusion

The measurement of landscape pattern from landcover maps has become a common practice in various disciplines such as landscape ecology. However, many people are unaware of the scale dependency of this phenomenon. This study demonstrates that the characterisation of landscape patterns by landcover maps is the product of the interrelationship between a number of scale dependent factors, such as spatial resolution, the application of smoothing filters, and the use of different study areas. Specifically, this study demonstrates that landcover maps will vary in terms of the extent and patchiness of classified areas based on the inter-relationship between these scale dependent factors. For example, the effect of using a majority filter at low spatial resolutions will not be the same when used at high or low resolutions. Techniques that are used at one resolution are not necessarily transferable to different resolutions and may result in a very different classification. This has wide ranging consequences for users transferring techniques used on medium resolution imagery from sensors such as Landsat to high resolution imagery from sensors such as IKONOS and Quickbird.

This study represents the first step in the development of a framework to quantify the magnitude of the effect of different spatial dependent factors on landcover classification. This study demonstrated that there is considerable interaction between scale dependent factors, indicating that investigations of spatial dependent factors need to be done simultaneously.

Future research is needed to assess the effect of these scale dependent factors on accuracy as well as patchiness and area. Furthermore, as the landscape patterns found in the study area may be site specific it is difficult to generalise to other areas. Thus, there is a need to perform the same spatial analysis for a wide range or spatial resolutions using different smoothing filters and extents in multiple real landscapes settings to create a significant volume of data. This will allow for wide ranging generalisations to be made which will be the basis for the development of guidelines for map users.

Chapter 5 Investigating species-environment relationships at multiple scales: differentiating between ecological operational scale and the modifiable areal unit problem.

Planned publication:

Lechner, A. M., W.T. Langford, S. D. Jones, S. A. Bekessy and A. Gordon, (preparation) Investigating pattern processes relationships at multiple scales: differentiating between scale of operation and scale of observation.

5.1 Introduction

Spatial scale is a central focus of research in ecology and its sub-discipline landscape ecology. Both the investigation of the scale at which landscape pattern generating processes operate and the scale dependency of the response of ecological systems to landscape pattern has received considerable attention (Levin 1992; Turner 1989). An understanding of the relationship between landscape pattern and ecological processes is central to research in landscape ecology with the aim of addressing key conservation issues such as the effect of habitat fragmentation on species diversity, abundance and persistence (Lindenmayer and Fischer 2007; Suter et al. 2007).

The identification of pattern-process relationships is confounded by interactions which change with scale, often in complex non-linear ways (Li and Wu 2004; Wiens 2002). Furthermore, these pattern-process relationships are difficult to identify because observed spatial patterns change with the scale at which an environmental property is sampled (Gustafson 1998). Thus, analysing the same phenomenon at different scales, such as when using remote sensing data from different satellite sensors, can lead to different results (Wiens 2002).

According to hierarchy theory, ecological systems are composed of relatively isolated, distinct scales operating simultaneously (O'Neill et al. 1989). Relationships found at one scale are not necessarily observable at another scale so every phenomenon needs to be measured at the appropriate scale (Turner et al. 2001). The scale at which ecological phenomena interact with or perceive the environment is known as the *operation scale* (Ecological phenomena includes processes such as pollination) (Dungan et al. 2002; Wu and Li 2006a). It is not always straightforward to determine the operation scale as often little is known about this relationship (Holland et al. 2004; Mayer and Cameron 2003). In some cases ecological phenomena operate at multiple scales and thus need to be observed and analysed at many scales (Levin 1992; Wiens 1989; Wu et al. 2006). The relationship between an ecological phenomenon and its environment can sometimes be completely overlooked if the incorrect scale is used (Saab 1997). For example, the effects of broad scaled environmental processes such as atmospheric flows or climatic processes are only observable at large scales while processes such as edge effects can only be observed at small scales (Bohning-Gaese 1997; Wiens 1989).

In order to determine the scale at which species-environment relationships operate, environmental measurements such as those describing landscape heterogeneity are measured at multiple scales and related statistically to ecological measurements. A common sampling design used to derive species-environment relationships is to sample ecological attributes (response variables) such as species diversity or population abundance at random points across a landscape and compare these to environmental measurements (predictor variables) calculated for the surrounding area within a circular buffer (e.g. Coreau and Martin 2007; Cushman and McGarigal 2004; Davis et al. 2007; Holland et al. 2004; Oneal and Rotenberry 2009; Pearman 2002; Suorsa et al. 2005). In order to perform this type of analysis at multiple scales the strength of the relationship is tested at various buffer sizes (henceforth this type of multi-scale sampling design is called the *multi-scale buffer area sampling*) (figure 5.1). Using this method the operation scale is then inferred as the buffer size at which the relationship between the ecological attribute and the environment measurement is the strongest (e.g. Coreau and Martin 2007; Holland et al. 2004; Pearman 2002; Suorsa et al. 2005).

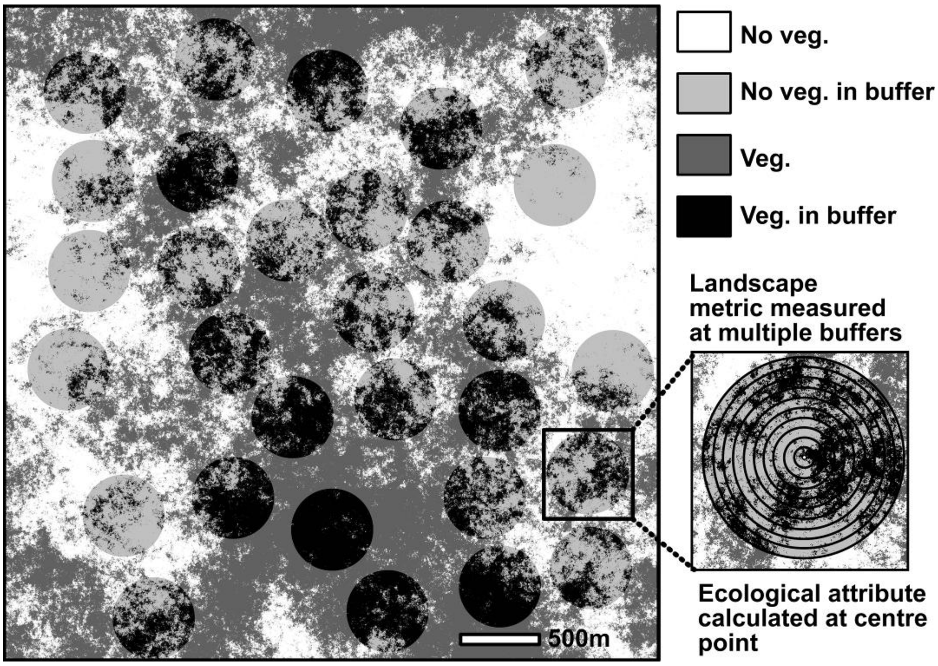


Figure 5.1 Multi-scale buffer area sampling design - Common sampling design for multi-scale studies in order to identify the operation scale. Ecological attributes such as species abundance or diversity are measured at point locations and environmental variables such as vegetation cover are measured within a circular buffer zone surrounding the point sample. Species-environment relationships are calculated at multiple buffer sizes through relating environmental variables to ecological attributes, commonly through some form of regression analysis.

In addition to being used to identify the operation scale, multi-scale analysis is also used to test the sensitivity of a statistical analysis to scale. In this case the statistical differences in correlation coefficients infers the robustness of the analysis to scale and indicate the presence of the modifiable areal unit problem (MAUP) (Openshaw 1984). The term MAUP is used to describe analyses affected by the arbitrary and modifiable size and shape of spatial units (Openshaw 1984). The MAUP can affect the results of analyses and render them meaningless (Jelinski and Wu 1996; Nelson 2001; Wu et al. 1997). In some cases, analyses using spatial units of different sizes and shapes can obtain nearly any correlation value (Fotheringham and Wong 1991).

Within ecology the MAUP is a particular case where the observation unit used to measure landscapes is commonly the square pixel of the remote sensing data. Ecological studies testing for the MAUP may use similar multi-scale experimental designs as studies which have the aim of identifying the operation scale. There is no difference in experimental design for studies with these two distinct aims, even though inferences made from the results of these studies differ. For example, differences in correlation coefficients found in studies testing for the MAUP are used to infer that a statistical analysis is not robust to scale. In contrast, studies searching for the operation scale (or the correct scale to measure a phenomenon) infer that differences in correlation coefficients are related to the response of an ecological phenomenon to particular scales.

5.1.1 Aim

The aim of this study was to test whether multi-scale analysis methods can be reliably used to identify the operation scale and if the effect of the MAUP would confound the results of these analyses. This issue is investigated using a simulated ecological model based on a multi-scale buffer area sampling technique with a known operation scale. Using a simulation model, the species response to the environment can be controlled and tested and the impact of the choice of remote sensing spatial resolution on the outcome of multi-scale ecological analyses can be quantified.

5.1.2 Background to the problem

A common aim for investigating species-environment relationships is to quantify the response of a species to the structural characteristics of their habitat and thus understand the implications of habitat loss and fragmentation. Habitat loss and fragmentation are two of the major systematic drivers of the decline and extinction of species worldwide (Brook et al. 2008; Fischer and Lindenmayer 2007). Fragmentation affects ecological processes such as the distribution and abundance of organisms, population persistence, species coexistence and species diversity (Griffiths et al. 2000; Levin 1992; Saunders et al. 1991; Suter et al. 2007; Turner et al. 1989). Multi-scale studies are often used to assess the scale at which fragmentation impacts on these ecological processes.

At different scales the relative importance of environmental variables (i.e. habitat) changes as the influence of the amount and configuration of these changes. The underlying ecological processes that create scale patterns are inferred by ecologists through the detection of different responses of these processes to environmental variables analysed at different scales (Krawchuk and Taylor 2003). The movement range of different organisms for dispersal and foraging is thought to be a key ecological process responsible for the generation of scale patterns (Addicott et al. 1987; Krawchuk and Taylor 2003; Mackey and Lindenmayer 2001; Wheatley and Johnson 2009). Spatial patterns of movement are associated with an animal’s food, shelter and reproductive requirements as well as minimising the effect of competition and predation (Mackey and Lindenmayer 2001). For example, Krawchuk and Taylor (2003) found that at scales similar to the movement range of individuals, patch size had the strongest relationship with population density, whereas at larger scales, patch isolation had the strongest relationship. Another ecological factor considered important in determining scale patterns is the relationship between home range size and the proportion of habitat available at different scales (Pearman 2002; Soderstrom and Part 2000). For example, Suorsa (2005) found that the relationship between forest cover and probability of occupancy for the Eurasian tree creeper was the strongest at scales associated with territory size.

There are many forms of multi-scale experimental designs used in ecology that investigate different elements of scale using a variety of spatial units. Multi-scale sampling spatial units range from natural hierarchies of ecologically scaled units such as populations and subpopulations (e.g. Krawchuk and Taylor 2003; Mackey and Lindenmayer 2001) to studies that vary only the remote sensing pixel size (e.g. Saura 2004; Wu et al. 1997). In this study we consider scale to be made up of three components: the *operation scale, observation scale* and *scale of the analysis* (Dungan et al. 2002) (see box 5.1 for definition of key terms used throughout this chapter).

The first component of scale, the *operation scale* is an emergent property of an organism's relationship with its environment. The operation scale is measured indirectly through the observation of scale and directly by changing the size and shape of the units in the experimental design. In ecological studies the spatial units used to sample both the ecological attributes and environmental data can change with scale.

The *scale of the analysis* (or in some cases *modelling scale*) refers to the units that are used in analyses (Dungan et al. 2002; Wu and Li 2006a). In our study it refers to the buffer size of the area surrounding a point. It is often based on some aspect of a species ecology e.g. home range size. For studies using the multi-scale buffer area sampling design, buffer sizes typically range from 20m-2000m (e.g. Holland et al. 2004; Pearman 2002; Suorsa et al. 2005).

The *observation scale* describes the size, shape, extent and distance between observational units used to sample a phenomenon (Dungan et al. 2002; Wu and Li 2006a). The observation scale is affected by a number of scale dependent factors ranging from spatial resolution (Wu et al. 1997) to thematic resolution (Buyantuyev and Wu 2007). Commonly, the observation scale for studies using a multi-scale buffer area sampling design vary from >1m pixel size for aerial photography (e.g. Wheatley et al. 2005) to ~30 to 60m for Landsat TM (e.g. Pearman 2002).

The effect of observation scale on ecological models, specifically spatial resolution, was the focus of this study. Spatial resolution is the primary factor influencing the classification of remote sensing landcover data (Tatem et al. 2002; Woodcock & Strahler 1987). It limits the smallest identifiable area in an image (Tatem et al. 2002) by affecting the size and the information content of the sampling units. In raw unprocessed raster data, spatial resolution is often considered to be equal to pixel size (Atkinson 2004). Spatial resolution can be subdivided into two components: 1) the pixel size and 2) the area on the ground that contributes to the value of a pixel. Ideally the value of a pixel would correspond to the area on the ground which it covered. However, the information content of a pixel is not only determined by landcover corresponding to its location, it is also affected by landcover found in neighbouring pixels as determined by the point spread function of the sensor (Cracknell 1998; Fisher 1997) and the methods used to process data. Landcover found in the centre of a pixel, has a proportionally greater contribution to its value than landcover found around the edge of a pixel.

Pre and post-processing of a remote sensing image using smoothing filters or resampling increases the influence of the values of the neighbouring pixels affecting spatial resolution. Common smoothing filters include the low pass and majority filters. Smoothing filters are commonly used in remote sensing to increase global classification accuracy by decreasing the salt and pepper effect caused by per pixel based landscape classification schemes or to remove noise caused by sensor error in raw remote sensing data (Ivits and Koch 2002; Zukowskyj et al. 2001). Furthermore, images are smoothed as a result of the practice of resampling, conducted routinely for geometric correction (georectification) or image registration (Cracknell 1998).

Most studies investigating species-environment relationships will use remote sensing data and the choice of observation scale will introduce spatial uncertainty in the characterisation of landscape pattern for the environmental data. Fine scaled sampling resolution can obscure coarse grained landscape patterns; while coarse grained sampling can miss fine scaled patterns as they become averaged out in larger sampling units. Landscapes may appear fragmented at one scale and continuous at another (Lechner et al. 2008). Furthermore, at larger observation scales ecologically important landscape structures such as small remnant vegetation and linear strips may not be extracted or extracted inaccurately (Lechner et al. 2009).

Box 5.1 Definitions of key terms.

Definition of key terms:

Observation scale: The sampling unit used to measure the environment e.g. pixel; sometimes referred to as the sampling scale or measurement scale.

Analysis scale: The scale at which an ecological analysis is conducted. Equivalent to buffer size.

Operation scale: The scale at which an ecological process interacts with the environment, also known as the *scale of phenomenon* or *characteristic scale* (Dungan et al. 2002; Wu and Li 2006a). This is the scale at which highest correlation values between environmental and ecological data occur.

True observation scale: The correct pixel size to sample an ecological phenomenon.

True landscapes: Landscapes at the true observation scale.

Apparent landscapes: Landscapes that are not at the true observation scale (e.g. incorrect pixel size or smoothing filter applied).

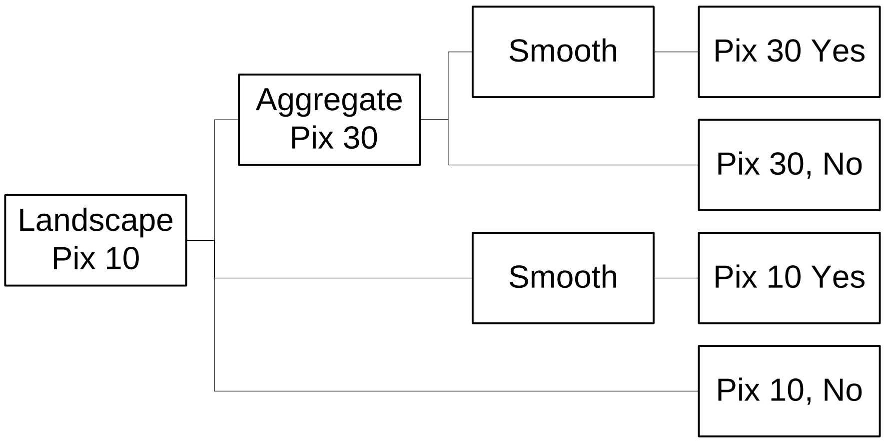
Derived ecological relationship: A term used to describe the synthetic dependent variable in the simulated species-environment relationship. Can be considered analogous to ecological attributes such as population abundance or species diversity.

Vegetation cover: The independent variable calculated from synthetic and real data predicting the ecological attribute's value. This value is based on the amount of vegetation recorded in the buffer area.

5.2 Method

In order to test for the effects of the MAUP on the identification of operation scale we simulated species-environment relationships and used real and synthetic landscapes. The simulation model was made up of 3 parts: 1) *landscape generator* 2) *sensor and classification simulator* and 3) *ecological model simulator*. Simulating the complete process from the generation of landscape pattern to the ecological models eliminates all uncertainty present when using real data. The truth can be known and deviations from the truth can be measured. Figure 5.2 describes the complete process of generating and sourcing the landscapes and the processing of the real and synthetic data.

a)



b)

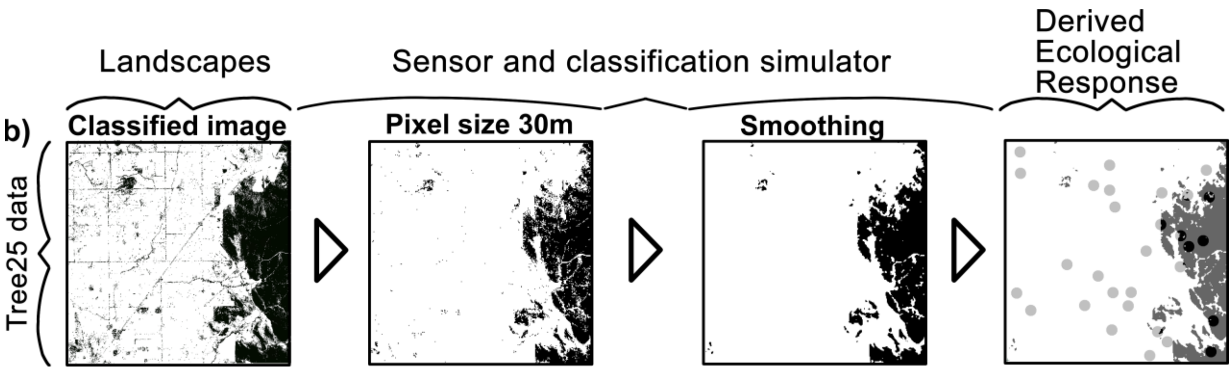


Figure 5.2 Flow diagram and example images describing the processing of real Tree25 and synthetic images to generate multiple landscape representations (n=24). a) Each real landscape (real A…F) and synthetic image is processed using the sensor and classification simulator to produce 4 different representations of each landscape, where Pix is the pixel size and yes / no refers to the application of the smoothing filter. b) In this example, the landscape Real C has been aggregated to 30m from its original 10m pixel size and a smoothing filter has been applied.

5.2.1 Landscape generator

The landscape generator is the first part of the simulation model. It generated both synthetic landscapes and sampled real landscapes. Real landscapes used in the simulation model were a mix of random and stratified sampled subsets of the regional Tree25 presence / absence tree cover data set produced for the Department of Sustainability and Environment's Corporate Geospatial Data library (DSE 2006). The dataset is derived from SPOT panchromatic imagery with a 10 metre pixel size, classified using a combination of digital classification and visual interpretation. The dataset covers most of the state of Victoria in Australia with an area of 227,416 km². Initially, 20 random subsets of the Tree25 datasets were created and then six of those subsets (henceforth, called Real A, Real B…Real F) were chosen so that a range of proportions of tree cover were sampled (Figure 5.3). The six 10 x 10 km subsets represent a range of landscape patterns with proportions of tree cover ranging from 9.5% to 62.3%. The subsets were from fragmented landscapes that are either dominated by agriculture or at the interface between agriculture and natural areas. A range of ecologically important landscape elements were intentionally included, such as small remnant patches and linear strips.

Real A	**Real B**	**Real C**	**Real D**	**Real E**	**Real F**
9.5% cover	9.5% cover	23.4% cover	32.0% cover	51.1% cover	62.3% cover

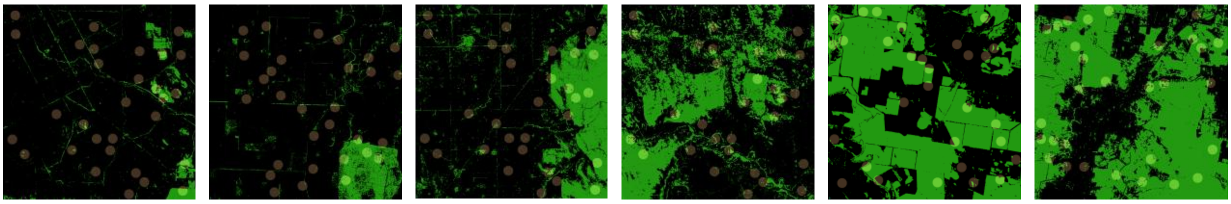


Figure 5.3 Tree presence /absence landscapes used in the model with percentage tree cover indicated below the landscape title. Woody tree cover represented as green and no tree cover represented as black. The 30 sampling locations for the ecological model are indicated on the map by circles. The circles represent the maximum buffer size of 500m diameter used in the ecological model.

Synthetic gray scale / continuous landscapes were generated using Saupe's (1988) fractional Brownian motion with midpoint displacement (midpointfM2D) algorithm implemented in the programming language IDL (See Appendix A for code). The same algorithm is used in many common synthetic landscape generation programs such as RULE (Gardner 1999) and the recent version QRULE (Gardner and Urban 2007). The midpointfM2D algorithm can randomly generate synthetic multi-fractal landscapes using a variety of fractal dimensions determined by the parameter H, ranging from 0 to 1. In map terms the fractal dimension equates to landscape patterns with different levels of spatial autocorrelation:

H = 0 - negative spatial autocorrelation
H = 0.5 - no spatial autocorrelation
H =1 - positive spatial autocorrelated.

Maps were generated for H values of 0.1, 0.5 and 1.0 to systematically test for the effect of a range of spatial autocorrelations and fragmentation on the outcome of the ecological simulation. Maps with lower H values appear more fragmented than those with higher H

values. The landscapes generated had a size of 1000 x 1000 pixels and a single pixel was considered equivalent to 10m pixel size in real terms. Thus the size of the synthetic landscapes was 10km x 10km; the same size as the real landscapes.

The generated synthetic landscapes were then classified using a binary classification scheme with two classes representing habitat and non-habitat which in this study is considered equivalent to the vegetation cover and no-vegetation cover. This is a common classification scheme used in landscape ecology to represent the patch-matrix geographic model (Antrop 2007). The images were thresholded so that a proportion of the total landscape area was assigned vegetation/habitat (*proportion*). The assigned *proportion* values were 0.25 and 0.5. The *proportion* value of 0.75 was not tested as landscape spatial patterns with this value were equivalent to the *proportion* value of 0.25 for the purposes of assessing spatial uncertainty in this analysis. The fractal nature of the synthetic landscapes results in differences in analyses only when both vegetation and no-vegetation have unequal proportions; whether vegetation or no-vegetation has the largest proportion is irrelevant.

5.2.2 Sensor and classification simulator

Next, both the synthetic and the real landscapes were used in the sensor and classification simulator to create different representations of the same landscapes. The first part of this simulation process involved aggregating the original pixel size of both the real and synthetic landscapes creating different representations of the same landscape. The images were aggregated based on a majority rule from their original 10m pixel size to 30m pixel size to simulate other remote sensing sensor pixel sizes (Table 5.1).

Table 5.1 Pixel sizes tested in the simulation model for both real and synthetic landscape data and equivalent satellite sensor.

Pixel size (m)	**10**	**30**
Equivalent remote sensing pixel size	SPOT XS	Landsat TM / ETM+

In the final step of the sensor and classification simulator a majority filter was applied to smooth the real and synthetic data to create another representation of the same landscapes. Using a majority filter decreases spatial resolution simulating the effect of pre and post-processing remote sensing images for either resampling or the application of a smoothing filter. A majority filter is commonly used during post processing of classified images (Lu and Weng 2007). The majority filter uses a 3 x 3 moving window filter to replace cells in the centre of the window based on the value that is in the majority (Figure 5.4).

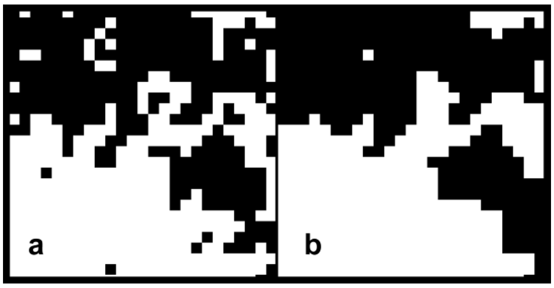


Figure 5.4 Effect of applying a majority filter: a) Original image, b) Smoothed imaged. There is a loss of fine scaled fragmentation in the smoothed image (b) compared to the original image (a).

5.2.3 Ecological model simulator

The final part of the whole model simulated a correlated ecological response by defining a linear function and then generated values for the ecological response based on this function. If the multi-scale buffer area sampling design is robust it should be able to recover the original linear relationship regardless of the scale of the remote sensing data. Following previous studies we used a simple univariate species-environment relationship modelled at at a range of scales (e.g. Holland et al. 2004; Pearman 2002; Taki et al. 2007). In this study correlation was calculated using Spearmen's *r* as the assumption for linear regression was not met because the distribution of vegetation fraction cover from each the plot data in each of the landscapes was often non-normal and plots of the residuals demonstrated that the data was often heteroscedastic. The *ecological response* in this study was derived from vegetation fraction cover using a simple linear function: $y = mx + c$ where $m = 1$ and $c = 0$. Thus, the final function defining the ecological response was $y = x_{BL}$ where *y* is the *derived ecological response* and x_{BL} is vegetation fraction cover at buffer radius *B* in meters with a landscape representation of pixel size *L*. The value of *B* corresponds to the true *analysis scale*, occurring at a specific buffer radius and the value of *L* corresponds to the true pixel size occurring at a specific pixel size.

In ecological studies using similar multi-scale buffer area sampling designs, buffer size is measured for a continuum of values (e.g. Holland et al. 2004; Pearman 2002) and the *ecological scale* is identified as the buffer sizes at which peaks in high correlation values occur. With this definition multiple scales of operation may be identified, however we simulated an ecological response that had a single *ecological scale*. Thus, if the species-environment relationship is derived with a buffer size and pixel size that match the sizes at which the ecological response was derived (e.g. at *B* and *L*) the resulting correlation coefficient, *r*, value will be 1. This is the *true ecological scale.* If the buffer size is changed the correlation coefficient will decrease. In this study for cases where two or more buffer sizes have the maximum value (i.e. in cases where the shape of the curve plateaus and does not peak) the ecological scale is identified as the average of the maximum range of these values.

Within each buffer area vegetation fraction cover was measured, a common explanatory variable used to assess the impact of vegetation cover on ecological attributes such as occupancy (Suorsa et al. 2005), population abundance (e.g. Heikkinen et al. 2007; Holland et al. 2004) and species diversity (e.g. Lawler et al. 2004; Pearman 2002). The *derived ecological response* is considered analogous to these ecological attributes. Vegetation fraction cover was measured at multiple buffer radii ranging from 25m to 250m.

The ecological response was derived using a subset of all the buffer radii (*B*), 25m (1964m^2), 125m (49087m^2) and 225m (159040m^2). The number of samples for each buffer size per landscape was 30, similar to many landscape-level studies (e.g. Pearman 2002; Taki et al. 2007). We used non-overlapping buffers which is commonly practiced in ecological experiments. This non-overlapping constraint reduces the effect of spatial autocorrelation and avoids violating the assumption of independence for regression models.

We quantified the effects of the MAUP on the identification of the ecological scale in a multi-scale ecological analysis by comparing results using a range of landscapes with pixel sizes that do and do not match the pixel size at which the ecological response was originally derived. Landscapes with pixel sizes that match the pixel size at which the ecological response was derived are termed true landscapes. Landscapes that use other pixel sizes and/or have a smoothing filter applied are termed the apparent landscapes. A total of 44 apparent landscapes were created using the real and synthetic landscapes with a range of spatial autocorrelations (H values), pixel sizes, proportions and smoothing filters (Table 5.2). An analysis is robust to changes in pixel size if the ecological scale identified is similar regardless of whether true or apparent landscapes are used. Furthermore, there should not be large changes in the shape of the curve of correlation values versus buffer sizes.

Table 5.2 Summary of the factors used to generate true (a) and apparent landscapes (b). The factors in table (b) with a † correspond to different methods used to generate true landscapes. The factors with a * correspond to ways in which the apparent landscape may be represented.

a) **True landscapes**

	***H* value / source data**	**Pixel size**	**Proportions**	**Total**
Synthetic	0.1, 0.5, 1.0	10,30	0.25,0.5 (n=2)	12
Real	Real A...F	10,30	n/a	12

b) **Apparent landscapes**

Dataset	***H value / source data*** †	**Pixel size***†	**Proportions (*P*)** †	**Smoothing***	**Total *n***
Synthetic	0.1, 0.5, 1.0	10,30	0.25,0.5	yes/ no	24
Real	Real A...F	10, 30	N/A	yes/ no	24

5.3 Results

The strength of the relationship between vegetation cover and the derived ecological response changed with buffer radius and pixel size. For example, figure 5.5 (landscape Real F) presents two out of 240 sets of scatter plots produced in this study used to describe the relationship between vegetation fraction cover and the derived ecological response. Figure 5.5a show the correlations generated when the pixel size matched the pixel size at which the ecological response was derived. The derived ecological response was calculated at a buffer radius of 125m and thus the correlation coefficient was 1 and there was a perfect linear relationship. This buffer size is identified as the ecological scale. When buffer size increased or decreased the relationship between vegetation fraction cover and the ecological attribute became weaker and the slope of the curve changed.

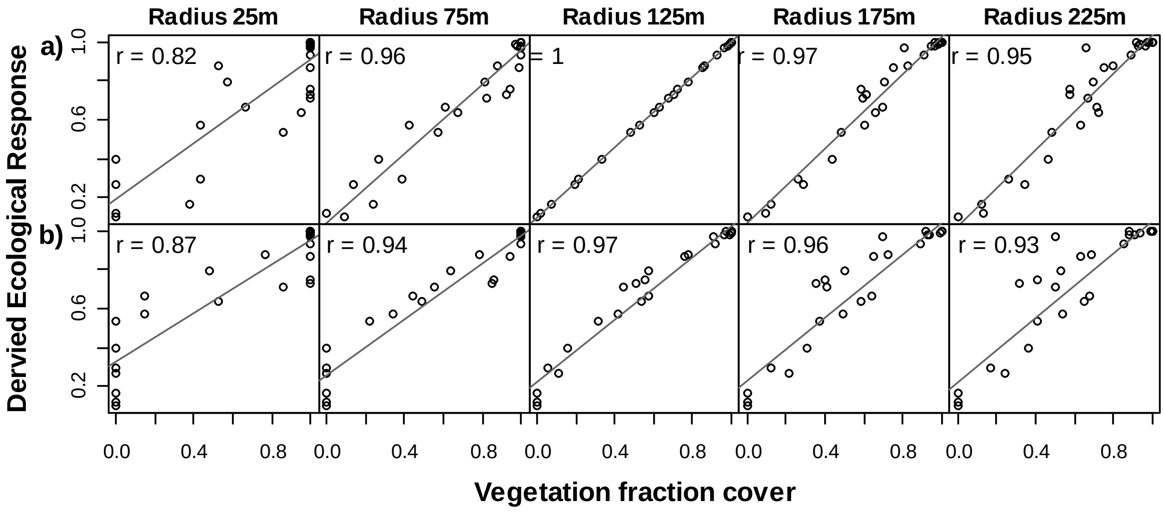


Figure 5.5 Scatter plots of vegetation cover (%) versus derived ecological response for landscape F. The ecological response has been derived using a pixel size of 10m and the buffer radius of 125m. The line of best fit plotted in dark gray and Spearman's *r* is presented in the top left corner. a) Observation scale: 10m pixel size and no smoothing filter. b) Observation scale: 30m pixel size with smoothing filter applied.

Figure 5.5b illustrates the effect of using an observation scale that differs from the true observation scale (i.e. using an apparent landscape) on the statistical relationship between the ecological attribute and vegetation fraction cover. In this case the operation scale identified did not change, however, the strength of the relationship was weaker for most buffer sizes. Furthermore, the line of best fit plotted was not as good an approximation of the true linear y=x relationship.

Figure 5.6 show scatter plots for another landscape, Real D, which demonstrate how the identified operation scale can change when apparent landscapes were used. Figure 5.6a show the correlations generated when the true landscape was used. The correlation coefficients are high for most buffer sizes and the operation scale is identified at buffer size 125m with an *r* value of 1. As with the previous scatter plots presented in figure 5.5a and figure 5.5 b, as the analysis scale changed from the true analysis scale and the observation scale differed from the true observation scale the correlation coefficients decreased (Figure 5.6a). Changing the pixel size by using an apparent landscape with a pixel size of 30m compared to a pixel size of 10m at which the ecological response was derived and applying a smoothing filter resulted in incorrectly identifying the ecological scale at a buffer size of 175m (Figure 5.5b). At this radius the highest correlation coefficient of 0.90 was recorded.

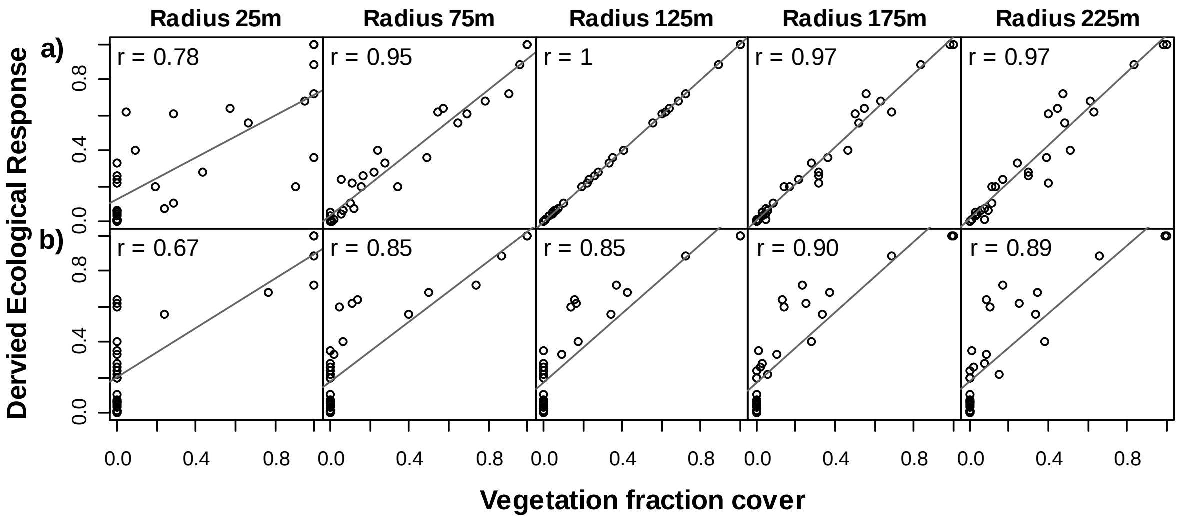


Figure 5.6 Scatter plots of vegetation cover (%) versus derived ecological response for landscape D. The ecological response has been derived using a pixel size of 10m and the buffer radius of 125m. The line of best fit plotted in dark gray and Spearman's *r* is presented in the top left corner. a) Observation scale: 10m pixel size and no smoothing filter. b) Observation scale: 30m pixel size with smoothing filter applied.

The scatter plots presented in figure 5.5 and Figure 5.6 can be summarised as a single curve describing the correlation coefficient versus buffer radii for the true and apparent landscapes (Figure 5.7). This is a common method of depicting the relationship between buffer size and correlation (e.g. Holland et al. 2004; Pearman 2002). However, most studies use a single spatial resolution and test multiple buffer sizes which is equivalent to a single curve in figure 5.7.

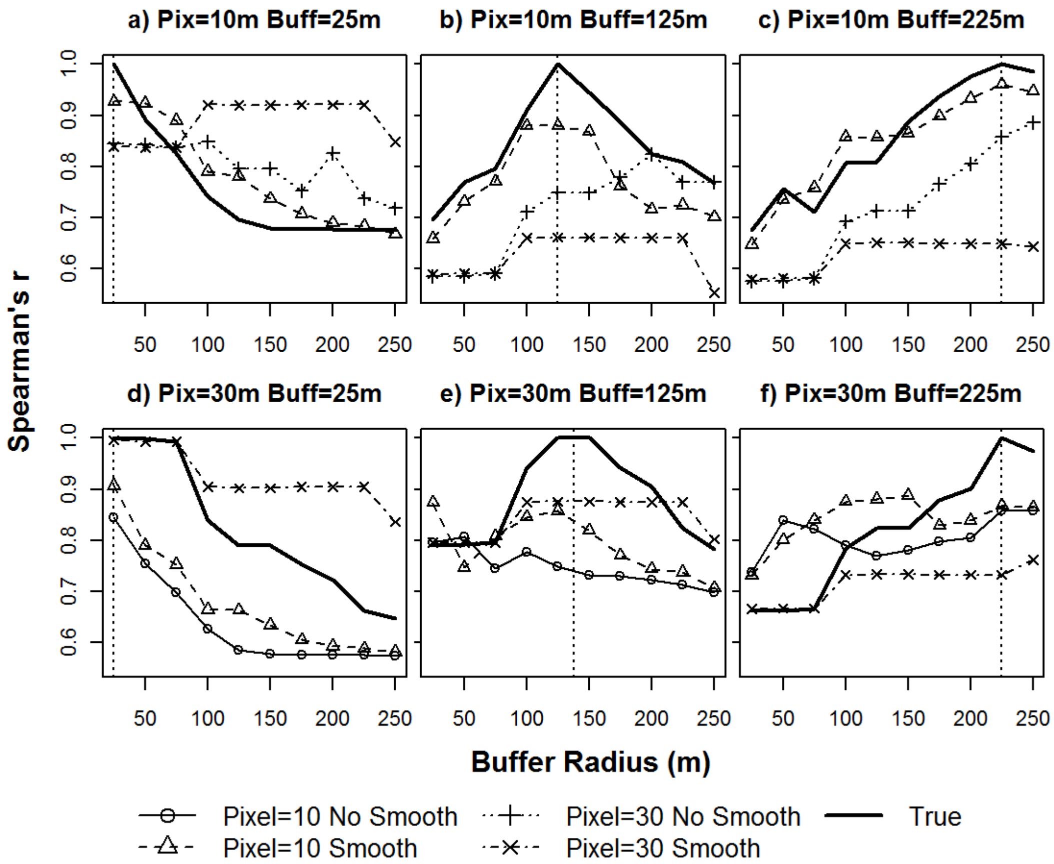


Figure 5.7 Graph of r values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for real landscape B. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.

The effect of the MAUP is illustrated by comparing curves describing correlation coefficient versus buffer radii for apparent landscapes to curves for true landscapes. Using apparent landscapes decreased correlation coefficient across all buffer radii and sometimes results in the misidentification of the ecological scale.

Not only do correlation coefficient values change with the use of apparent landscapes, but so do the shapes of the curves. In some cases the shape of the curve can change greatly, from a simple exponential to a complex polynomial resulting in the appearance of multiple peaks in the curve indicating two or more scales of operation rather than a single ecological scale as represented by the true landscape. For example, for Real B with an ecological response derived with a pixel size of 10 and a buffer radius of 25m, the true ecological scale is 25m, when using an apparent landscapes with a pixel size of 30 and no smoothing filter applied there are two peaks in correlation coefficient values indicating operations scales at buffer radii of 100m and 200m (Figure 5.7).

The effect of only applying the smoothing filter was dependent on the pixel size at which the ecological response was derived and the pixel size of the apparent landscapes. The application of the smoothing filter usually had little effect on correlation coefficients when the pixel size of the apparent landscapes pixel size at which the ecological response was derived, when the pixel size was 10m (e.g.Figure 5.8a Pixel size=10m, compare the curve with the smoothing filter applied and without). However, when the pixel size of apparent landscapes differed from the pixel size at which the ecological response was derived the application of a smoothing filter usually decreased all the correlation values and sometimes changed the identified scale of operation (e.g. Figure 5.8a Pixel size=30m, compare the curve with the smoothing filter applied and without).

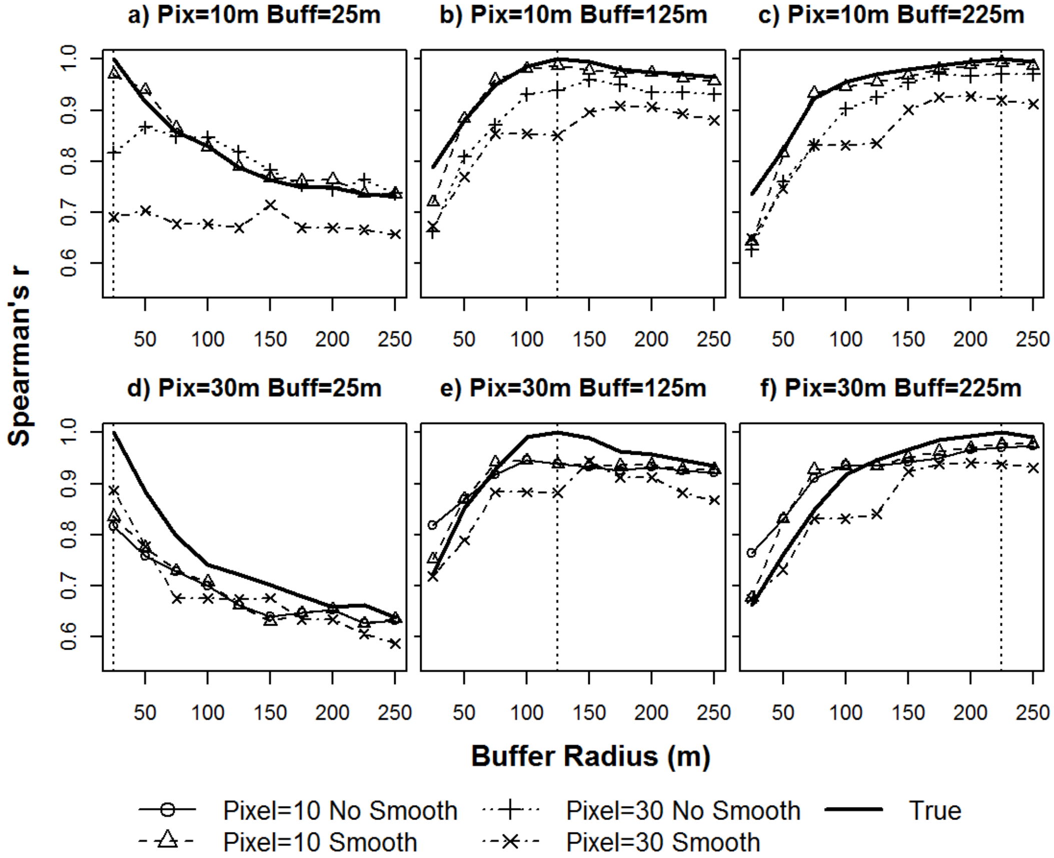


Figure 5.8 Graph of *r* values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for real landscape D. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.

For some landscapes such as Real D the effect on analysis of using apparent landscapes was negligible for some combinations of pixel sizes and buffer sizes at which the ecological response was derived and was visible for others. For example, there was no difference in the operation scales identified and the shape of the curve was similar regardless of the apparent landscape used for Real D with an ecological response was derived with a 30m pixel size and 225m buffer (Figure 5.8f). Other combinations of pixel sizes and buffer sizes used to derive the ecological response affected the shape of the curve and/or on the scale of operation identified. For example, when the ecological response was derived with a 10m pixel size and 25m buffer size and an apparent landscape with a pixel size of 30m with a smoothing filter applied the identified operation scale was 150m instead of the true operation scale of 25m (Figure 5.8a).

For some real landscapes using apparent landscapes did not greatly affect the outcome of analyses (Figure 5.9). The only effect of using apparent landscapes on real landscape E was a systematic decrease in the correlation values over all buffer sizes. The calculated operation scale was the same whether apparent landscapes were used. Furthermore, the shape of the curve remained similar regardless of the apparent landscapes used.

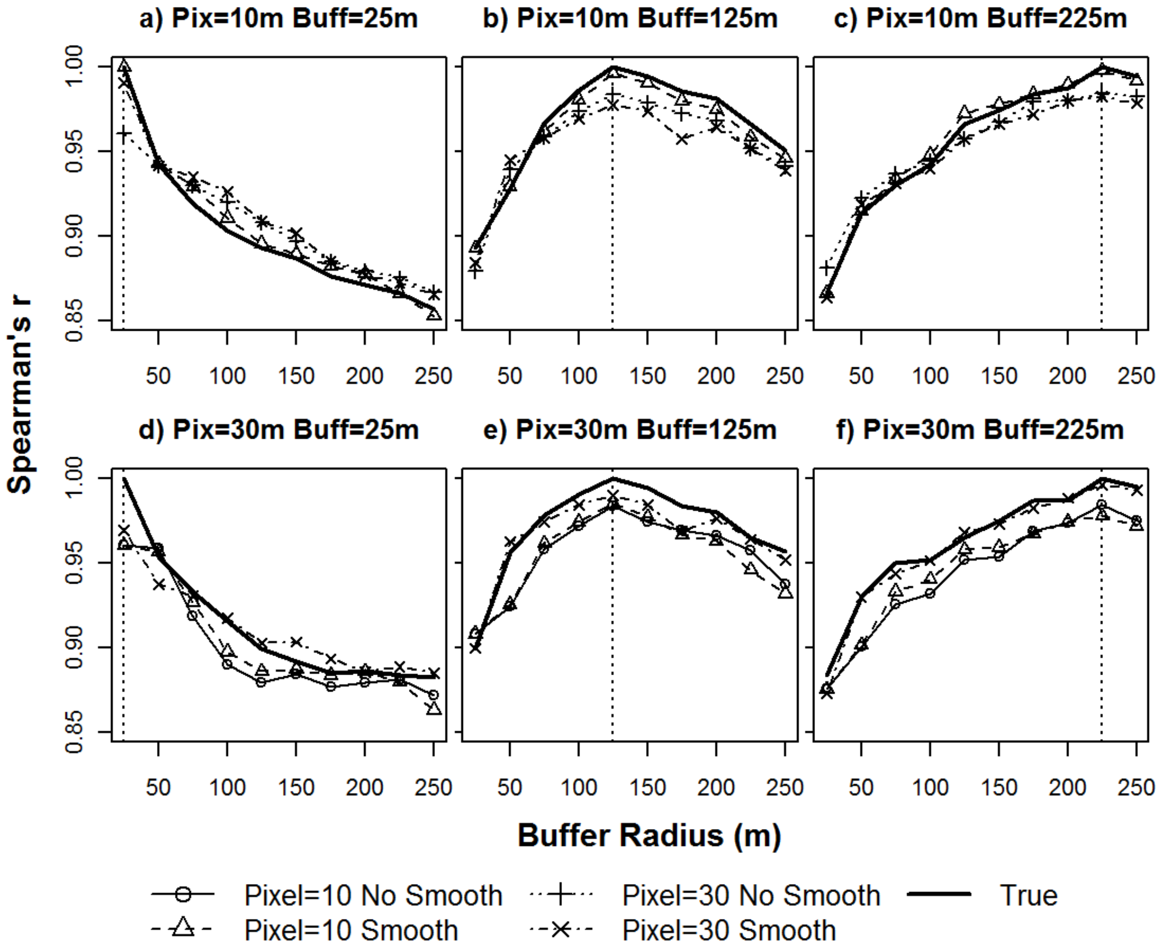


Figure 5.9 Graph of r values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for real landscape E. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the r values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.

The effects of using apparent landscapes varied between real landscapes and within landscapes depending on the buffer and pixel sizes used to derive the ecological response.

Both pixel size and the application of the smoothing filter affected whether analyses were robust to changes in analysis scale (Real A…F)(Appendix B).

In contrast to the real landscapes, the synthetic landscapes were qualitatively not as greatly affected by the use of apparent landscapes. In many cases there was very little reduction in the correlation values across all buffer sizes and smaller errors in the measurement of operation scale (Figure 5.10**,** Appendix B). This is in contrast to the great variability and inconsistency in the effects of using apparent landscapes for the real landscapes (Real A..F). When using apparent landscapes the shape of the curve did not vary as greatly for synthetic landscapes compared to real landscapes. The effect of buffer sizes on r was much weaker with synthetic landscapes than the real landscapes. However, some synthetic landscapes such as H=0.1 P=0.25 did have similar levels of error in the operation scale identified and qualitatively similar changes in the shape of the curves due to the use of apparent landscapes (Figure 5.11).

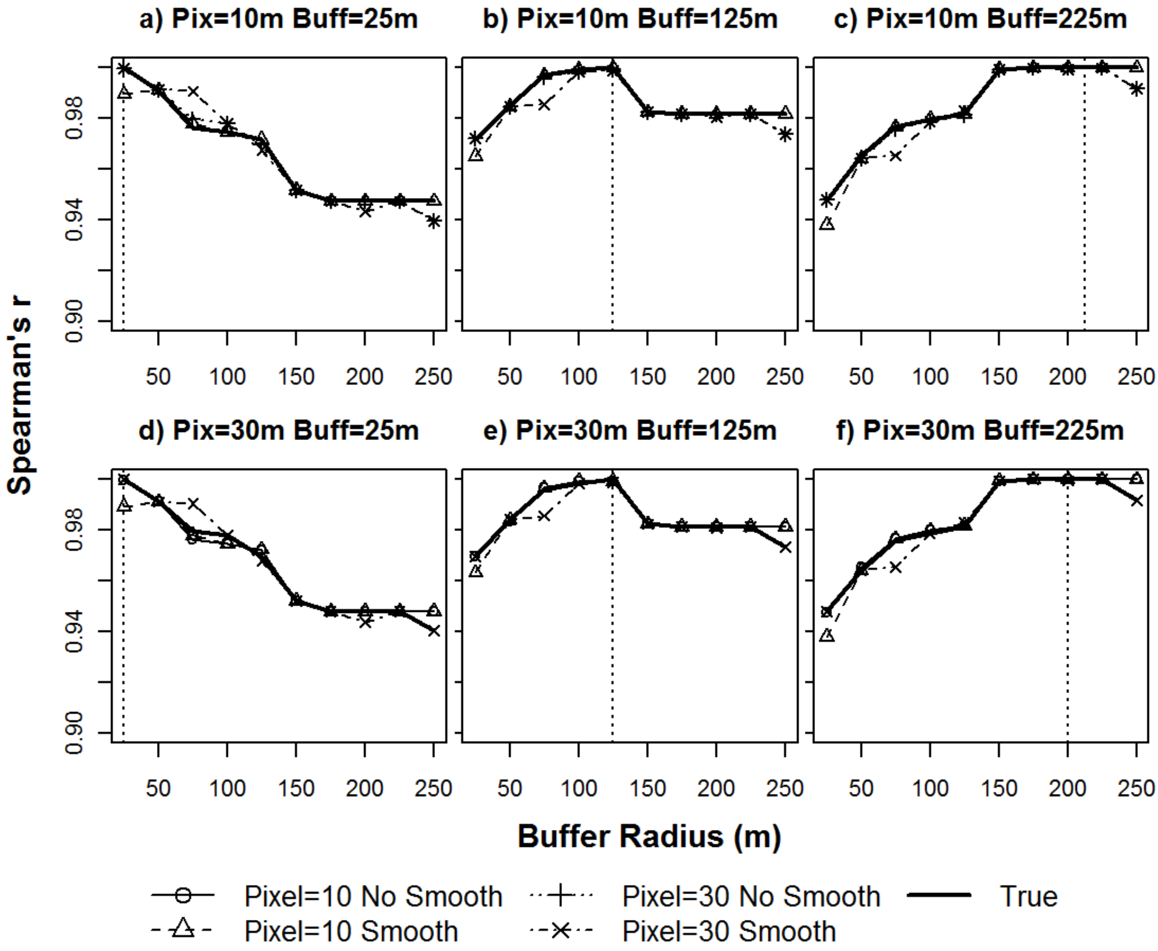


Figure 5.10 Graph of r values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for synthetic landscape H=1.0 P=0.5. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the r values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.

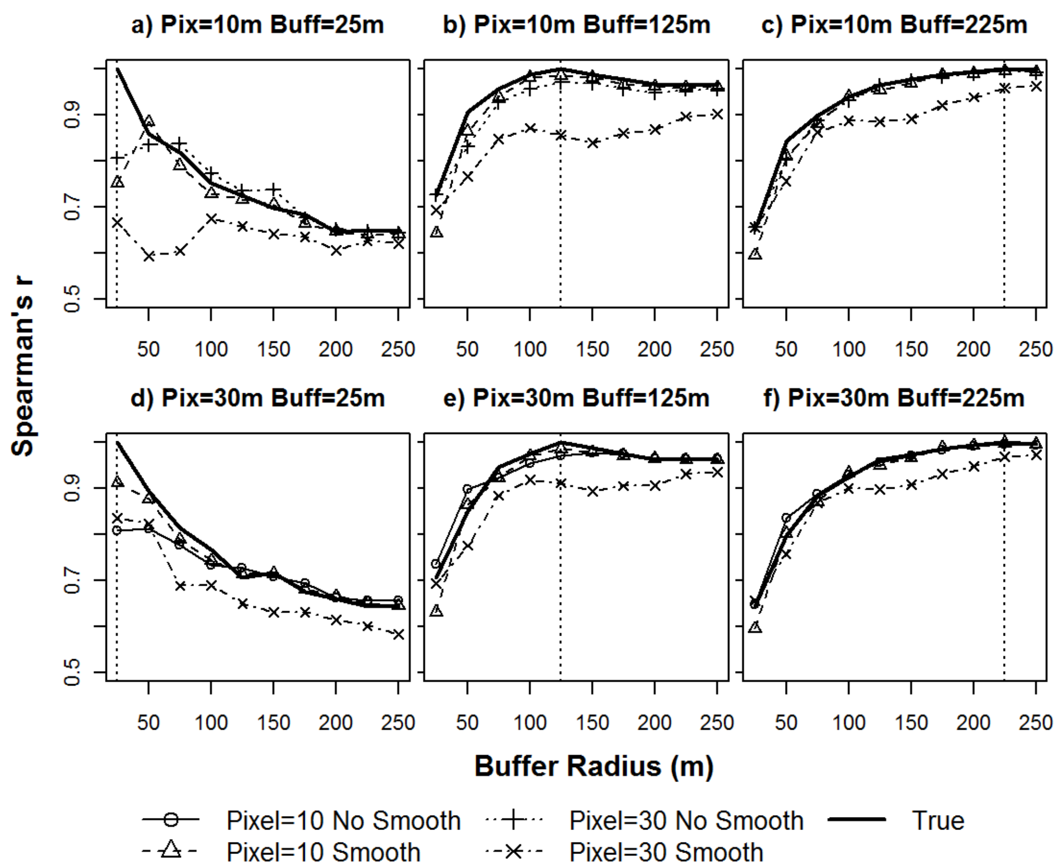


Figure 5.11 Graph of *r* values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for synthetic landscape H=0.1 P=0.25. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.

Figure 5.12 and figure 5.13 summarises the output from the simulation model by comparing the highest and lowest identified operation scale and comparing these to the true operation scale for all buffer and pixel sizes used to derive the ecological response. The previous plots shown in Figure 5.5 - 5.11 presented interesting subsets of all the simulation model output presented in figure 5.12 and figure 5.13. For example, figure 5.7a corresponds to figure 5.12b, buffer size 25 and pixel size 10.

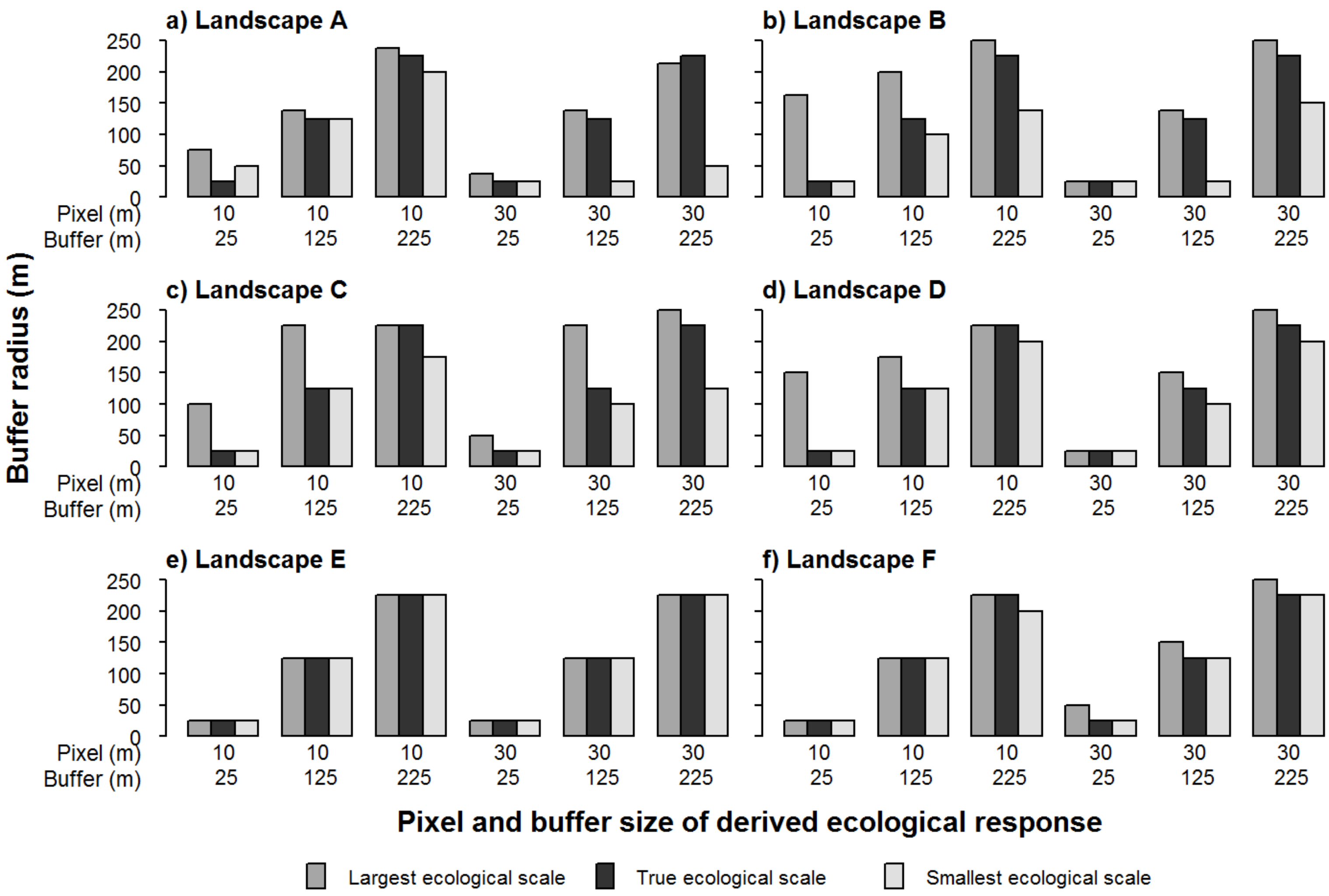


Figure 5.12. Comparison of buffer radii (y-axis) for the largest, smallest and true operation scale identified for a range of ecological responses (x-axis) for landscapes real A…F. Pixel and buffer sizes used to derive the ecological response described on x axis.

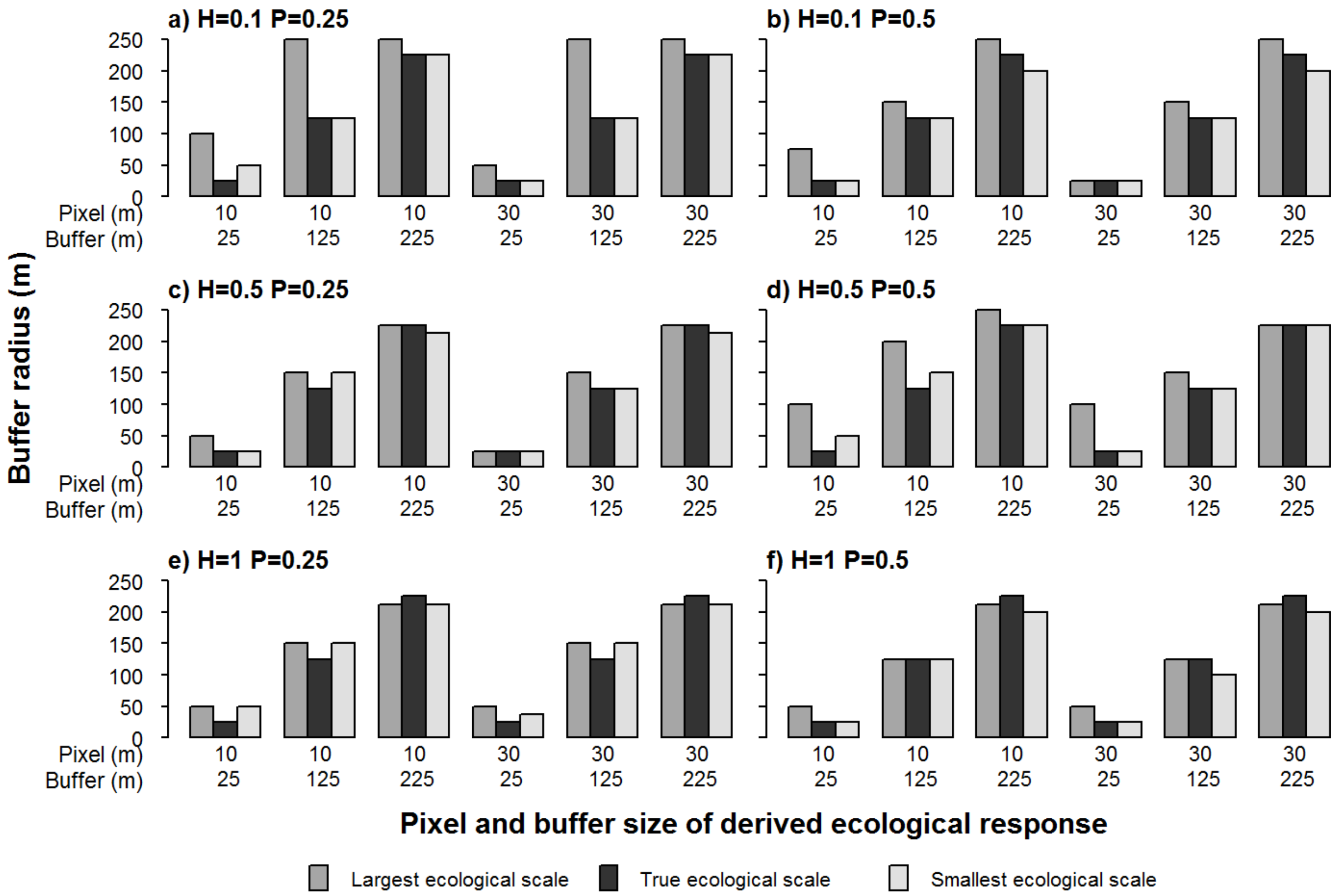


Figure 5.13 Comparison of buffer radii (y-axis) for the largest, smallest and true operation scale identified for a range of ecological responses (x-axis) for synthetic landscapes. Where H =spatial autocorrelation and P=proportion of habitat. Pixel and buffer sizes used to derive the ecological response described on x axis.

The effect of using apparent landscapes on errors in the measurement of operation scale varied between landscapes and within landscapes dependent on the buffer and pixel size used to derive the ecological response. For some landscapes such as Real E, Real F, H=1 P=0.5 and H=1 P=0.25 there was little or no effect of using apparent landscapes on identifying the operation scale for any combination of true observation or true analysis scales (Figure 5.12 and figure 5.13). The differences between real and synthetic landscapes were not as apparent when only comparing differences in errors in the measured operation scale. The effect of using apparent landscapes for real landscapes appeared less predictable than the synthetic landscapes. Real landscapes appear to have greater variability within landscapes on errors in the measurement of operation scale as a result of different buffer and pixel sizes combinations used to derive the ecological response. In the same landscape there may be very small differences of 0-25m for most buffer and pixel size combinations used to derive the ecological response and large differences of 125m for other combinations (Figure 5.12d).

The synthetic landscapes appeared to show some predictability with regard to the effect of spatial autocorrelation and proportion of vegetation. Positively spatially autocorrelated landscapes with vegetation cover (P) of 0.5 appeared to be more robust to the effects of using the apparent landscapes than landscapes with zero spatial autocorrelation, negatively autocorrelation and/or lower vegetation cover.

5.4 Discussion

The results of this study demonstrate that spatial uncertainty arising from scale has the potential to produce misleading results in ecological analyses. It found that the observed ecological responses repeatedly exhibited the MAUP, these responses were not just a property of the analysis scale (buffer size) but also the scale at which the environment was sampled (pixel size). There was large variability in the effect of using apparent landscapes on the accuracy of the identified ecological scales between landscapes and for different combinations of pixel size and buffer size used to derive the ecological response. In some cases, differences in pixel size only affected the strength of the relationship between the ecological attribute and environmental variable. In other cases the ecological scale was misidentified with errors ranging from 0 to 150m where 225m is the maximum measured by this study. Furthermore, in some instances multiple ecological scales were identified when in reality there was only a single ecological scale.

The effect of using apparent landscapes is an example of the MAUP. In some cases using apparent landscapes only affected the strength of the relationship between the ecological attribute and environmental variable. In these cases the MAUP can be considered to have no effect on the identification of operation scale as it was unaffected by the observation scale used to represent the landscape. In other cases, the strength of the species-environment relationship decreased and the operation scale measured was erroneous. In these cases the results of the analyses were spurious, indicating the presence of the MAUP.

5.4.1 Impact of landscape pattern on spatial uncertainty

This study found that landscape spatial heterogeneity may be an important factor in determining whether spatial uncertainty arising from observation scale affected analyses. Synthetic landscapes that are more highly fragmented with lower H values and real landscapes that qualitatively appeared spatially heterogeneous were less robust to changes in observation scale than synthetic landscapes with high spatial autocorrelation (high H value) and/or *P* values of 0.5. Thus, landscape pattern may not only be an important driver of ecological processes but a driver of spatial uncertainty. The unpredictability in the effects observation scale for the real landscapes is a major concern for ecologists because they are likely to be present in most real data used for published studies. Critically, much of the research conducted in landscape ecology is in fragmented environments similar to those represented by the real landscapes and thus analyses may be more susceptible to spatial uncertainty.

The robustness of some of the synthetic data to observation scale is in contrast to Li et al (2005) which found that changing the observation scale of synthetic landscapes resulted in large differences in the measurement of landscape pattern using landscape metrics. This suggests that the measurement of landscape pattern using landscape metrics may be more sensitive to spatial uncertainty than the multi-scale experimental method tested in this study. Studies using synthetic landscapes generated with the fractional Brownian motion algorithm commonly used in landscape ecology may not capture the complexity and diversity of spatial patterns that occur when using real landscapes. Thus, studies using synthetic data to simulate real landscapes may underestimate the effects of spatial uncertainty on analyses.

Synthetic landscapes generated with fractal algorithms may be less susceptible to the effects of scale as they exhibit self-similarity at multiple scales. Thus spatial patterns in synthetic landscapes may appear uniform over the whole landscape. This is in contrast to real landscapes that have been fragmented by human impacts which often have gradients and regionalised variations (anisotropy). Furthermore, real landscapes often display more regular geometric patterns than the patterns produced by landscape generators based on fractal algorithms (e.g. Real E). A similar phenomenon has been found by other authors (e.g. Emilio

Rafael et al. 2009; Shen et al. 2004), whereby the effects of scale were found to be greater in real landscapes than synthetic landscapes. Similarly, Riitters, Vogt et al. (2007) found patterns generated using synthetic RULE (midpointfM2D algorithm) landscapes were different to patterns that were found with real landscapes. Further investigation is needed using more complex synthetic landscape generation methods that include anisotropy (e.g. Gardner and Urban 2007), different synthetic landscape generation techniques that can represent geometric anthropogenic features such as agricultural and urban cover and road networks (e.g. Walters 2007) and techniques that use a combinations of synthetic landscape algorithms and real landscapes (e.g. Hargrove et al. 2002). Synthetic landscapes, however, are still useful in testing for the effect of measured changes in landscape pattern through the varying *H* and *P.*

5.4.2 Scale and ecological analysis

The results of this study are relevant to both multi-scale and single scale ecological analysis. In many cases ecological studies are conducted at a single scale using both a single analysis and observation scales. In these cases the observed responses of a phenomenon to environmental variables at a particular scale may be stronger or weaker due to a mismatch in scales or spurious due to the effect of the MAUP. If the observation scale and analysis scale match the operation scale of a phenomenon the true response of a phenomenon to environmental data may be derived. This study has confirmed empirically what other authors have suggested, that using a single scale can result in phenomenon going undetected and the derivation of flawed relationships (e.g. Jelinski and Wu 1996; Wiens 2002; Wiens 1989).

Our study tested commonly used pixel sizes in landscape ecology based on standard remote sensing sensors and demonstrated that the choice of pixel size can affect analyses. Landscape scale research is typically only conducted at fixed scales, often arbitrarily determined by readily available generic data sets or sensors without any investigation of the sensitivity of analysis to arbitrary scales (Comber 2008; Pontius et al. 2008; Schmit et al. 2006). The use of the default sensor may ultimately be worse than making a subjective judgement about the scale at which a phenomenon operates (Pontius et al. 2008).

The most common recommendation in landscape ecology in order to address the effects of scale is to conduct studies at multiple scales (Levin 1992; Wiens 1989; Wu et al. 2006) using the multi-scale sampling designs as investigated in this study. However, our results suggest that the relationship between the operation, analysis and observation scale varies along a continuum. Wheatley and Johnson (2009) reviewed 79 multi-scale wildlife habitat studies published since 1993 and found that in addition to the initial biologically justified scale chosen (i.e. home range size), the other scales tested, usually one larger and one smaller, were often arbitrarily chosen. Our study showed that the response of species to scale may change at multiple analysis scales, often abruptly, and that studies using a small selection of analysis scales may lead to incorrect conclusions being drawn due to the absence of data at untested scales.

The typical method used in landscape ecology of systematically changing the observation or analysis scale (as used in this study) can test for the sensitivity of analyses to scale. However, there is no guarantee that observed patterns at a particular scale are not spurious due to the presence of the MAUP. Hence, if scale sensitivity is detected it is impossible to know whether this is the result of the operation scale or the MAUP. In this study we used a simulation model and thus there was a known truth based on the simulated ecological relationship to use as a benchmark to measure accuracy. When conducting ecological analyses using real data, the true ecological scale is a property of the scales at which a phenomenon is measured and there is no method of knowing the accuracy of the analysis. Further research using both real ecological and environmental data is required to whether the results of this study are evident in real studies and to what degree.

5.4.3 Simulation modelling: simplifying complex ecological relationships

This study used a simulation model to investigate the effects of pixel size on measuring the ecological scale and its relationship with landscape pattern. Simulated data allows some elements of the complexity of real world phenomena to be studied. It allows for the control of all aspects of the pattern-process relationship from the generation of landscape pattern to its effects on ecological processes. Our simulation model represents an optimistic scenario for conducting ecological analyses, where there was no unknown uncertainty in the spatial data or in the ecological model. There was no measurement error and all the parameters and statistical relationships were known. Additionally, the true landscapes represent the true geographic representation that perfectly describes how the species perceives the environment. These relationships can never be known with absolute certainty when using real data and ecologists can only make inference about causal processes based on empirical data. In studies using real data the effects of spatial uncertainty on ecological analyses are likely to be much greater and more difficult to distinguish than in simulation studies. If simple theoretical relationships cannot be derived correctly using simulation models, there can be little confidence in recovering these from real data (Austin et al. 2006).

In comparison to other empirical studies using real data which have conducted similar types of multi-scale analyses on a continuum of scales, the shape of the curves of buffer size versus correlation coefficient in this study appear to be much smoother, although qualitatively similar (e.g. Holland et al. 2004; Pearman 2002). However, the derived correlation coefficients were much higher in our simulation model with a consistently smaller range than other studies. The maximum range of r for any landscape tested in this study our study was approximately 1.0 to 0.57. Other studies investigating the relationship between an ecological attribute and vegetation cover had larger range and smaller r values e.g. Holland et al. (2004) calculated Pearson's r values of ~0.3 to 0.0, Pearman (2002) calculated r^2 values of ~0.7 to 0.35 and Taki et al.(2007) r^2 derived values of 0.165 to 0.045. Additionally differences between buffer sizes and correlation coefficients tended to be weaker for the simulation model compared to real studies. For example, landscape Real D with an ecological response derived using a pixel size of 10m and buffer size of 225m at a buffer size of 25m the *r* value was 0.73 while for all buffer sizes greater than 50m values ranged from 0.93 to 1 (Figure 5.8c). Much higher and smaller differences in *r* values between buffer sizes would be expected with a simulation model as there was only a single factor affecting pattern-process relationship unlike in these real models where there are likely to be multiple unmeasured ecological factors obscuring relationships. Comparison between this study and other studies is made difficult due to the variety of measurements of correlation such as r^2 and Pearson's *r* used.

There are many sources of uncertainty in species-environment relationships originating from the model choice and parameters and the environmental and ecological data. For example, ecological relationships may be non-linear and difficult to derive statistically because of confounding factors such as spatial autocorrelation (Legendre et al. 2002; Wintle et al. 2005). Our study used a simple univariate linear model to describe the species-environment relationship as used by other authors (e.g. Holland et al. 2004; Pearman 2002; Taki et al. 2007) but many ecological studies use multiple explanatory variables described by data from multiple sources at different scales. Furthermore, scale dependent factors that create spatial uncertainty include many other factors not tested in this study such as minimum mappable units, thematic resolution and scale of landscape units (Buyantuyev and Wu 2007; Lechner et al. 2009; Wu et al. 2000). These untested forms of spatial uncertainty and model error have the potential to amplify the impact of remote sensing spatial uncertainty arising from scale on ecological analyses.

The binary habitat maps utilised in this study are commonly used in landscape ecology (Antrop 2007). There are many forms of error that result from the process of generating binary habitat maps that were not investigated in this study. Spatial uncertainty can be the result of many other factors such as classification error (e.g. Langford et al. 2006; Shao and

Wu 2008) and variations and ambiguity in landcover class definitions (e.g. Colson et al. 2009; Comber et al. 2005b). For example, Langford et al. (2006) found that in some cases map classification error can cause a thousand-fold increase in error in the calculation of landscape metrics. These non-scale related sources of spatial uncertainty are likely to further degrade analyses results.

Ecologists spend considerable effort testing uncertainty in ecological data (Chapman et al. 2005), while often ignoring the effects of spatial uncertainty. Users of spatial datasets often blindly accept them as error free (Adams and Gillespie 2006; Evans 1997), even though uncertainty in spatial data may in some cases be as important or more important than errors in other model parameters (Schmit et al. 2006). Previous studies comparing the impact of spatial uncertainty versus model or parameter uncertainty show that both may impact on ecological analysis. However, whether spatial or non spatial factors are a greater source of error may depend on the specific study. For example, a study by Ruckelshaus et al. (1997) found that their model was more sensitive to error in model parameters compared to spatial inputs. Conversely, Minor et al. (2008) found that the habitat map was the largest source of error for her spatially explicit population model. Thus, to ensure ecological studies are robust to uncertainty, there is a need for testing of spatial data to become as common as testing for uncertainty in non-spatial model parameters.

5.4.4 Future work

Further research is needed to expand on the findings of this study to develop methods that reduce and quantify spatial uncertainty, further develop the simulation model and investigate this phenomenon with real ecological data. Spatial uncertainty arising from scale can be the result of the simple categorical, often binary, landcover classification system commonly used in ecology. Investigating the use of more complex robust landcover classification methods in ecology such as fuzzy classifiers that can describe sub-pixel landcover area (Robinson 2007) and/or re-scalable spatial data that is scale invariant (Gardner et al. 2008) may reduce the effect of the MAUP. Along with more robust landcover classification schemes, multi-scale uncertainty analysis methods need to be developed that improve on the existing sensitivity analysis that can't identify differences between the effects of scale dependence of ecological phenomenon and the MAUP. Further investigation is needed to assess the effect of the MAUP on a wider range of ecological models that have non-linear and/or multivariate relationships and more scale dependent factors. These further studies may prove that instances where the MAUP caused flawed analyses are far more frequent than demonstrated in this study.

5.5 Conclusion

This study used simulation modelling with real and synthetic spatial data to investigate whether multi-scale ecological analysis methods can be reliably used to identify the ecological scale. It found that the common practice of conducting multi-scale studies in order to identify the ecological scale can in some cases produce flawed results because of the effects of the MAUP. Thus, multi-scale ecological analyses may not be able to distinguish scale patterns caused by the relationship between an organism and its environment and scale patterns resulting from the MAUP. This study provides further evidence that the ecological analyses conducted at single or multiple scales may not be robust to the effects of scale. Without the incorporation of uncertainty arising from scale, ecological analyses using remote sensing data will continue to produce results with unquantified uncertainties.

Chapter 6 Synthesis

6.1 Summary

This thesis investigates the effect of spatial uncertainty in remote sensing data on ecological analyses. Uncertainty originates in the representation of landcover and propagates to spatial analyses. Specifically, this thesis investigates spatial uncertainty arising from scale, demonstrating quantitatively the effects of scale on the characterisation of landscape pattern and ecological analysis (Chapters 3, 4, 5). The importance of spatial uncertainty within landscape ecology is not widely appreciated and rarely addressed (Chapter 2), but this thesis demonstrates important implications for ecological analysis commonly used in the discipline. In some cases spatial uncertainty can obscure observed pattern and process relationships potentially leading to spurious results when conducting multi-scale analyses (Chapter 5). Potential future directions for research in the disciplines of remote sensing and landscape ecology in order to deal with issues of spatial uncertainty are provided in this concluding chapter.

6.2 Research questions

6.2.1 Are landscape ecologists addressing spatial uncertainty when conducting analyses?

Chapter 2 presents a review and analysis of whether spatial uncertainty is being addressed or acknowledged within landscape ecology literature. The most frequently explored spatial uncertainty issues that affect the characterisation of landscape pattern and analysis is a group of five scale dependent factors and classification errors (pixel size, minimum mappable unit, smoothing, extent and thematic resolution). A systematic review of articles in the journal *Landscape Ecology* in 2007 found that most of these issues are not addressed and are rarely reported. Of the studies that addressed the effects of the scale dependent factors, very few investigated more than kind of spatial uncertainty.

The review found that in most cases, landscape ecologists accept remote sensing data at face value without investigating spatial uncertainty. In studies that didn't investigate the effects of scale, the default pixel size was generally used, with the majority of studies using either Landsat TM and ETM+ sensors with a ~30m pixel size or aerial photography with a ~1m pixel size. Generic, readily available datasets were commonly used, such as the European CORINE or USA's National Landcover dataset (NLCD). Data with arbitrary pixel sizes and classification schemes may not accurately represent landscapes at a scale relevant to the ecological question being asked, resulting in spatial uncertainty that may negatively impact on the results of spatial analyses.

6.2.2 How do scale dependent factors affect the characterisation of landscape pattern and how do they interact?

Chapters 3 and 4 investigate the effects of scale on the characterisation of ecologically relevant spatial pattern. Conventional methods for quantifying accuracy in remote sensing data using error matrices are inadequate for describing error and uncertainty in the characterisation of landscape pattern. These methods do not quantify variation in the spatial distribution and representation of landcover units resulting from scale. In landscape ecology, accurately characterising the spatial arrangement can be more important than correctly estimating the total area of a landcover class.

Chapters 3 and 4 investigate the effects of scale on the representation of landscapes using the patch-matrix geographic model most commonly used in landscape ecology. Chapter 3 investigates the effect of scale on the classification and extraction of small and linear patches, which often have greater ecological significance than their areal extent. Chapter 4 investigates the effects of scale on the characterisation of spatial pattern at the landscape scale.

Chapter 3 demonstrates that individual patches that are small and/or linear have proportionally higher classification error than larger more compact features. When the size of the patch approaches the size of the pixel, patches are lost as a result of the location of the grid with respect to the patch. This chapter demonstrates that the grid size should be many times larger than the size of the features in order to accurately extract them. For example, for square patches the grid pixel area has to be 11 times smaller than the patch size to achieve a mean classification accuracy of 75%.

Chapter 4 demonstrates that the characterisation of landscape pattern may change with the spatial resolution used; sometimes unpredictably. Using a coarser spatial resolution as a consequence of using larger pixels and smoothing filters results in fine scaled landscape pattern disappearing. Landscapes appear less fragmented, with less edge complexity and fewer patches, as small patches are lost or aggregated into larger patches. However, estimates of total class area remained constant regardless of scale. The effects of scale dependent factors on some components of landscape pattern (e.g. number of patches) were predictable in most cases. However, this was not always the case and the effect of changing pixel size or applying a smoothing filter was not consistent. This chapter demonstrates that scale dependent factors interact and may need to be considered simultaneously in order to quantify the extent of spatial uncertainty that results from scale.

6.2.3 How does scale in remote sensing data affect ecological analysis?

Chapter 5 investigates the effect of remote sensing data scale on using multi-scale species-environment models to identify the scale of operation (e.g. the scale at which an organism interacts with the environment). It found that in some cases the estimated scale of operation and the strength of the relationship between the derived ecological response and vegetation cover were unaffected by the scale of the remote sensing data. However, in many cases the strength of the relationship decreased and the scale of operation identified was incorrect, indicating the presence of the modifiable areal unit problem (MAUP).

This chapter found that the degree of spatial heterogeneity of a landscape is an important factor in determining whether remote sensing data scale affects ecological analyses. The impact of using landscapes with known error was greater for the real landscapes that appeared qualitatively more fragmented than synthetic landscapes. Synthetic landscapes that are more fragmented with lower vegetation cover were more affected by scale than less fragmented landscapes with 50% vegetation cover. The differences in the outcome of analysis resulting from using synthetic data versus real data indicates that synthetic landscapes may not adequately represent the range of landscape patterns that occur in reality.

6.3 Integration

This thesis demonstrates that there are fundamental problems with the way that spatial data uncertainty is dealt with in landscape ecology. The failure of landscape ecologists to address scale issues and the use of generic datasets and default pixel size has the potential to affect the results of ecological analyses. Chapter 3 demonstrates that many studies utilising the commonly used Landsat sensor are unlikely to pick up fine scale landcover units such as linear strips and patches, which are often considered ecologically important. Chapters 4 and 5 show that both the characterisation of landscape pattern and ecological analyses are affected by scale and in some cases, this will result in flawed analyses. Furthermore, chapter 5 demonstrates that highly fragmented landscapes are more susceptible to the effects of the MAUP than less fragmented areas. Many ecological analyses are conducted in highly fragmented landscapes as it is these environments that urgently need ecological understanding to prevent loss of biodiversity.

This thesis demonstrates the complexity of the problem of spatial uncertainty in landscape ecology. This complexity is likely to be one reason why spatial uncertainty is rarely being addressed in ecological analyses. In the initial review presented in chapter 2, five scale dependent factors and many other sources of spatial uncertainty were identified. Even though chapter 4 only investigated three scale dependent factors and chapter 5 investigated 2 of those factors, the effects on the characterisation of landscape pattern and ecological analyses were still apparent. Chapters 4 and 5 demonstrate that scale dependent factors interact; sometimes unpredictably. These chapters only investigated a subset of the factors identified because of the limits imposed by computer hardware. However, if more scale dependent factors were included in the analyses of chapters 4 and 5 it is likely that the effect of scale would have been considerably greater and more difficult to predict.

One of the greatest problems in understanding and addressing the impact of scale in landscape ecology is the difficulty of knowing the true scale that a phenomenon interacts with the environment. Throughout this thesis, the impact of scale was tested by creating multiple realisations of landscapes and measuring the differences in landscape pattern and its impact on ecological analyses. This method can only demonstrate the robustness of analyses to scale, but cannot identify the correct scale. An alternative approach is to use simulation models, as in chapter 5, where a known truth was defined by the simulation model. However, when investigating real ecological phenomena the true scale will always be a property of the measurement methods. Given the large differences and unpredictability in the characterisation of landscape pattern that occur as a result of scale, solutions to this problem are challenging.

6.4 Towards quantitative and robust analyses in remote sensing and landscape ecology

I finish this chapter with suggested guidelines for dealing with spatial data uncertainty to improve the theoretical foundations of both landscape ecology and remote sensing. Any solution to the problem will require a transdisciplinary approach that deals with uncertainty in representing landscapes (remote sensing) and in describing the influence of landscape on ecological processes (landscape ecology).

Both landscape ecology and remote sensing disciplines conduct research at the landscape scale and both suffer from a lack of quantitative theory. Theory in landscape ecology tend to be implicit or verbal, such as rules of thumb based on sound, real world observations; lacking the rigour and precision of theory that is mathematically based (Turner 2006; Vermaat et al. 2005; Wiens 2002). The focus of research in landscape ecology is not primarily on testing theory. Rather, landscape ecology tends to focus on a specific ecological phenomenon, deriving conclusions that may value laden and specific to a location (Vermaat et al. 2005; Wiens 2002).

Similarly, remote sensing lacks mathematical theory with regards to understanding the relationship between the outcome of landcover classification and the effect of landscape elements and heterogeneity on this outcome. Much of the focus within remote sensing research is on achieving the highest classification accuracy and there is often no quantitative investigation of the underlying factors that influence accuracy. Commonly, empirical methods are used in remote sensing to derive statistical relationships between multispectral remote sensing data and in situ landcover field observations (training data) to predict the values of landcover outside of the field observations for the rest of the study area. Remote sensing measurements of electromagnetic radiation are used as a surrogate for landcover measurements, when in reality they are measurements of the radiative transfer processes which is affected by such things as the geometric properties of the media (e.g. vegetation, soil) with which the radiation interacts (position, size, shape, orientation of the objects constituting these media), and the physical properties of the scatterers (e.g., aerosol phase function, leaf reflectance and transmittance, pigment concentration) (Verstraete et al. 1996). Thus, without an understanding of the radiative transfer process there is can be no formal understanding of how error arises when creating remote sensing maps.

Both landscape ecology and remote sensing tend to conduct research using a single or a small number of landscapes, leading to problems with generalising outside of the study area. For example one focus of research in landscape ecology is the identification of the smallest set of landscape metrics that can describe all of the different forms of landscape pattern (e.g. Cushman et al. 2008; Lausch and Herzog 2002; Neel et al. 2004). No consensus exists on the choice of metrics (McGarigal et al. 2002) and the results of some studies contradict each other (Cushman et al. 2008). The reason for the lack of consensus has been attributed to each study investigating a limited suite of landscape metrics on a different set of landscapes with their own unique landscape patterns characteristics (Cushman et al. 2008).

Simulation modelling can be used in conjunction with real data or as an alternative, to test theory and provide robust experimental design. Simulation modelling is useful in landscape ecology and remote sensing to overcome the problem of small sample sizes and the lack of “true” replication (Chen et al. 2008; Meyer et al. press). Simulation models also allow for the truth to be defined, in contrast to models based on real data, where the truth will always be a property of the measurement method. Furthermore, many spatially explicit studies that use real data need to be analysed using specialised statistical methods as replicates may not be independent due to spatial autocorrelation (Legendre et al. 2002; Schooley 2006). Simulation modelling can be used to overcome these issues associated with the complexity of real data (Li and Wu 2004; Meyer et al. press). Meyer (press) recommended using a combination of both empirical and simulation approaches so that the results will benefit from the realism of empirical data as well as the statistical power of simulations. Alternatively, the limitation of studies with very little replication can be overcome by meta-analysis of other unreplicated studies. However, this can be challenging because of differences in methods of classifying landscapes (Chen et al. 2008) such as the result of using different scales Wheatley and Johnson (2009) and differing ontologies (Lepczyk et al. 2008).

A promising direction to overcome the problems of uncertainty in experimental design in both remote sensing and landscape ecology is to use quantitative methods to develop explanatory models of the relationship between scale, error and landscape pattern. These models can be used to model spatial error and determine situations where error is likely to pose a significant problem. Few studies have considered how the numerous factors of scale, landscape pattern and classification error interact and affect the accuracy of spatial pattern characterisation and analysis. Exploring the pattern process relationship at multiple scales through designing effective experiments is challenging as experimental manipulation of environmental variables at the landscape scale is often impractical (Chen et al. 2008). Large sample sizes of real and synthetic landscapes are needed, such as those employed in this thesis, in order to develop explanatory models that describe this complex relationship.

Research could build on previous frameworks and explanatory models, such as the Strahler et al.'s (1986) L- and H-resolution model, to understand error and uncertainty in remote sensing data. This model describes the relationship between the size of objects in a scene, the pixel size and classification accuracy. Explanatory models such as the L- and H-resolution model are rarely used in remote sensing, and there is often no empirical justification for the choice of remote sensing techniques for a particular landscape other than it produced the highest classification accuracy.

The development of explanatory models for remote sensing error and uncertainty will enable a common framework to be applied across all remote sensing studies and allow for an understanding of the propagation of error to analyses. Modelling the sources of remote sensing uncertainty will allow for a systematic approach to determine the appropriate techniques to achieve a given classification and spatial pattern characterisation accuracy. There is a lack of research describing how these errors propagate through to the outputs of spatially explicit modelling in landscape ecology. A valid explanatory model is required to realistically predict how error will propagate through to end-use analyses. As classification error is not randomly spatially distributed across the landscape (Congalton 1988), understanding the factors that affect the representation of landcover maps will aid in understanding how error propagates. The explicit treatment of spatial uncertainty in ecological models need to become routine (Burgman et al. 2005).

Finally, an understanding of the effects of spatial uncertainty needs to be expanded further to examine the effects on policy and decision making (Figure 6.1) (Borgstram et al. 2006). Ecological research is often conducted at scales that are not meaningful to policy makers (Stevens et al. 2007) and conversely, management decisions are conducted at scales that bare little or no relation to the scale at which ecological processes are operating (Wiens 2002).

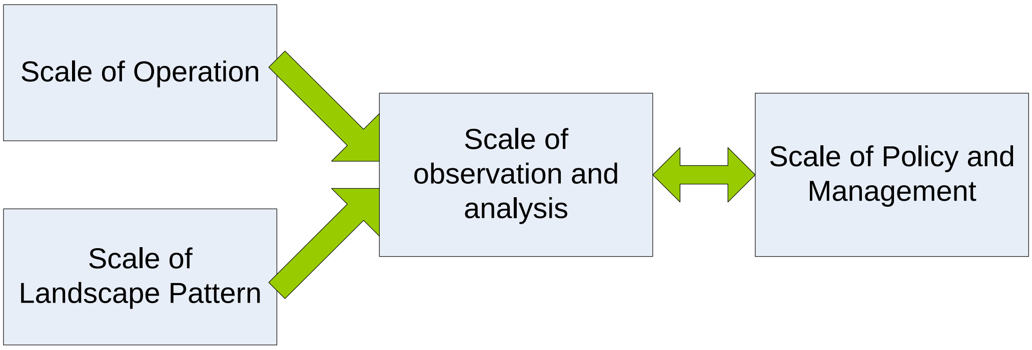


Figure 6.1 Propagation of spatial uncertainty originating from scale. This thesis concentrated on the first 3 components: scale of operation, scale of landscape pattern and scale of observation and analysis.

The treatment of remote sensing spatial uncertainty and its effects on ecological analyses need to be addressed by both the data users and producers due to its complex and transdisciplinary nature. As the complexity of both remote sensing and landscape ecology increases few users are likely to be experts in both, thus there is a need for collaborative approaches to issues of scale and error in spatial data in landscape ecology (Gergel 2007; Wiens et al. press; Wu and Hobbs 2002). Robust error propagation analysis is probably too difficult for 'ordinary' GIS users (Heuvelink 2002). This collaborative approach needs to be embraced by both communities in order to develop guidelines, methods and standards for spatial data production and use that are relevant to ecologists.

Spatial data standards (e.g. ISO 19100 Series, ENV12656, 1998) developed by the geospatial community provide a useful foundation for error reporting. However, the current reporting standards and practices are not useful in assessing fitness for use in landscape ecological research as they typically ignore error and uncertainty that affect the characterisation of landscape pattern. It is rare for example, for a map to explicitly represent uncertainty in spatial data (Schmit et al. 2006), even though the documentation of spatial data quality is widely recognised as important in order to use spatial data effectively (Worboys 1998). Much of the focus of data quality standards is on the concept of “fitness for use”, which, in practice is based on communicating uncertainty and error as opposed to methods of dealing with uncertainty or estimating error propagation. However, ecologists are restricted in the spatial datasets they use and may make use of data that imperfectly describes geographic phenomenon out of necessity, ignoring documented spatial data quality. Thus, there is a need in the geospatial community to not only focus on the documentation of accuracy and methods of creating more accurate maps, but to explore the consequence of inaccuracy on analyses conducted when using spatial data.

Finally, traditional hard classification schemes commonly used to represent the patch-matrix models used by landscape ecologists may be inadequate to represent the complexity of real landscapes. A collaborative approach is needed to investigate whether more complex representations of the landscape can be used to overcome the limitations of using remote sensing hard classification schemes. Some existing methods of representing landcover developed by the remote sensing community may deal with some of these spatial data uncertainty issues. As described in chapters 2 and 3, numerous landcover classification techniques are available to represent landscapes, such as fuzzy classification or soft classification techniques that have the potential to overcome some of the problems of scale. The reluctance to embrace these newer remotes sensing techniques probably stems from the increase in complexity in both producing and processing these datasets that may be beyond most landscape ecologists. Furthermore, in landscape ecology, the unit of analysis is most commonly the patch, thus soft classification methods are not always appropriate data input for models. A collaborative approach is needed to develop ecological models suitable for use with soft classification techniques, incorporating geostatistical approaches to analysing spatial pattern. The use of these more complex representations of landcover in landscape ecology is still rare (as shown in chapter 2) and requires substantial innovation.

6.5 Conclusion

This thesis has highlighted some of the spatial uncertainty issues prevalent when using remote sensing data in landscape ecology. It demonstrated that landscape ecologists rarely address spatial uncertainty even though spatial uncertainty arising from scale can have important impacts on ecological analyses. Several key findings emerged from this research.

Firstly, it found that mapping error was highest when the scale of the feature and the raster grid coincided. Ecologically important landscape elements such as small and linear vegetation patches of similar scales to the raster grid had lower classification accuracies, and were less likely to be extracted than larger more compact features. Secondly, this thesis showed that at coarser scales, subtle levels of patchiness declined. Small patches either aggregated into larger patches or completely disappeared. Thirdly, it demonstrated spatial uncertainty can obscure observed pattern and process relationships potentially leading to spurious results when conducting analyses using multi-scale species-environment. In conclusion, this thesis quantified the impact of scale on the classification of landcover maps and demonstrated how spatial uncertainty in the characterisation of landscape pattern can impact on ecological analysis.

This thesis should be considered a first step to addressing this issue that is transdisciplinary in nature and thus rarely a topic of research. The challenge for future research in both landscape ecology and remote sensing is to develop universal explanatory models that describe conditions where scale will be an issue and scaling models that can be used to overcome these issues. Without the incorporation of uncertainty arising from scale, ecological analyses using remote sensing data will continue to produce results with unquantified uncertainties, which may result in poor and/or ineffective management decisions.

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Appendix A

The following code was used to create the random multi-fractal synthetic images in IDL. For further information regarding the rest of the IDL and R code used for the rest of the simulation model in chapter 5 please contact the author directly (alexmarklechner@yahoo.com.au).

```
;Midpoint displacement and successive random additions in two dimensions (midpointfM2D)

;Adapted for IDL from pseudocode describing the midpoint FM2D published in:
;Saupe, D. (1988). Algorithms for random fractals. In H.O. Peitgen & D. Saupe (Eds.),
;The science of fractal images (pp. 71-113). New York: Springer-Verlag
; and
; RULE
;Gardner, R.H. (1999). RULE: map generation and a spatial analysis program. In K. J.M. & G. R.H.
;(Eds.), Landscape Ecological Analysis: Issues and Applications (pp. 280–303). New York: Springer

;ALGORITHM MidPointFM2D(X, maxlevel, sigma, H, addition, seed)

;Arguments--------
;maxlevel = maximal number of recursions, N=2^maxlevel
;sigma    = initial standard deviation = 1
;H        = parameter - determines fractal dimension D=3 - H
;addition = boolean parameter (turns random additions on/off)
;seed     =seed value for random number generator

;Variables--------
;i, N, stage = integers
;delta       = real number  holding standard deviation "delta =sigma"
;x, y, y0, D, d = integer array indexing variables

;Functions--------
;Gauss2
;f3(delta,x0,xl,x2)=(x0*x1+x2)/3 +delta*Gauss2
;f4(delta,x0,x1,x2,x3) =(x0+xl*x2+x3)/4 + delta * Gauss2
```

```
;Output--------
;Array of real numbers



;****************************************
Function Gauss2, val1, sigma,seed
;****************************************
;create a normal number by summing 12 uniform random numbers
sum = 0.0
for i = 1,12 do begin
        sum = sum + randomu(seed)
endfor

GaussVal = (sum - 6.0) *  sigma + val1 ; Original method

return, GaussVal

end

;****************************************
Function f3,delta,x0,x1,x2,sigma,seed
;****************************************
returnnum = ((x0+x1+x2)/3) + (delta*Gauss2(0.0,sigma,seed))
return,returnnum
end

;****************************************
Function f4,delta,x0,x1,x2,x3,sigma,seed
;****************************************
returnnum = ((x0+x1+x2+x3)/4) + (delta*Gauss2(0.0,sigma,seed))
return,returnnum
end

;****************************************
Function MidPointFM2D, maxlevel,sigma,H,addition,wrap,gradient,seed
```

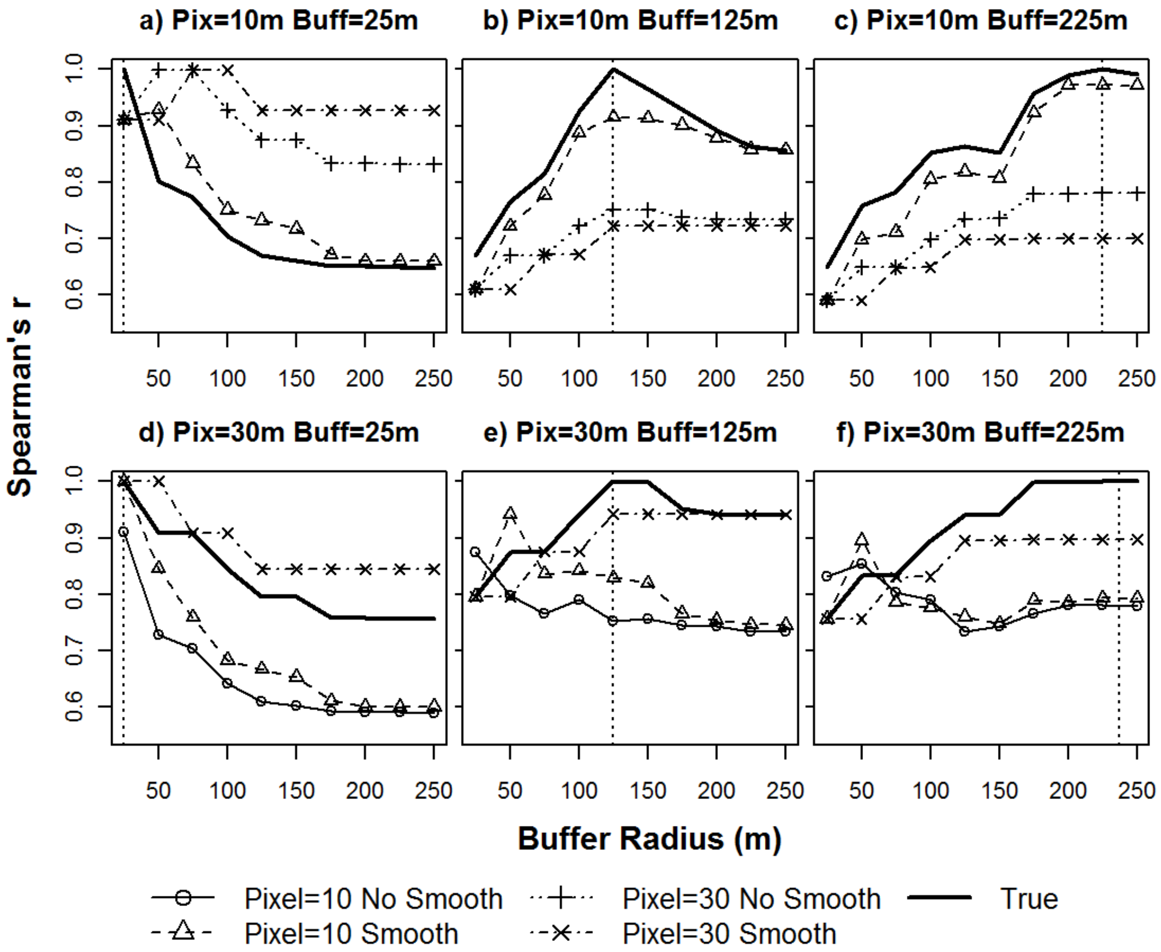
```
;*****************************************
;Example of how to use function:
;x=MidPointFM2D(8,1,.5,0,1,0,0,1)
;print, x

;Arguments parsed to Pro MidPointFM2D

;maxlevel=8 ; maxlevel determines the size of the image
;sigma= 1.0
;H= 0.1
;errorcheck=0 ; if errorcheck is 1 then variable values will be printed as the program runs
;addition=1 ; if addition eq 1 then run extra code
;wrap=1 ;Wrapper basically makes the top and bottom rows mirror images of each other.
;Gradient=0; if gradient equals 1 the corners will ansiotopic image will be created
        northeast = 59
        southeast = 20
        southwest = 10
        northwest = 40

;print, "program running"

;Setup array
N=2^maxlevel

;/* set the initial random values for the corners */
delta = sigma

;setup corners
GRID(0,0)= delta*Gauss2(0.0,sigma,seed)
GRID(0,N)= delta*Gauss2(0.0,sigma,seed)
GRID(N,0)= delta*Gauss2(0.0,sigma,seed)
GRID(N,N)= delta*Gauss2(0.0,sigma,seed)

if Gradient eq  1 then begin
        GRID(0,0)= northeast
        GRID(0,N)= southeast
        GRID(N,0)= southwest
```

```
        GRID(N,N)= northwest
        print,"northeast = ", northeast
        print,"southeast = ", southeast
        print,"southwest = ", southwest
        print,"northwest = ", northwest
endif

D = N
dd =N/2

for stage = 1, maxlevel do begin     ;FOR variable = init, limit [, Increment] DO BEGIN ****loop 1
        ;going from grid type I to type II
        delta = delta * 0.5 ^(0.5*H)

        ;#1 interpolate and offset points
        for x = dd, N-dd, D do begin
                for y = dd, N-dd, D do begin
                        GRID(x,y) = f4 (delta, GRID(x+dd,y+dd), GRID(x+dd,y-dd), GRID(x-
                        dd,y+dd), GRID(x-dd,y-dd),sigma,seed)
                Endfor
        Endfor

        ;#2 displace other points also if needed
        if addition eq 1 then begin
        ;print, "addition being implemented 1"
                for x=0, N, D do begin
                        for y=0, N, D do begin
                                GRID(x,y) = GRID(x,y)+delta*Gauss2(0.0,sigma,seed)
                        Endfor
                Endfor
        endif

        ; going from grid type II to type I
        delta = delta * 0.5 ^(0.5*H)

        ;#3 interpolate and offset boundary grid points
```

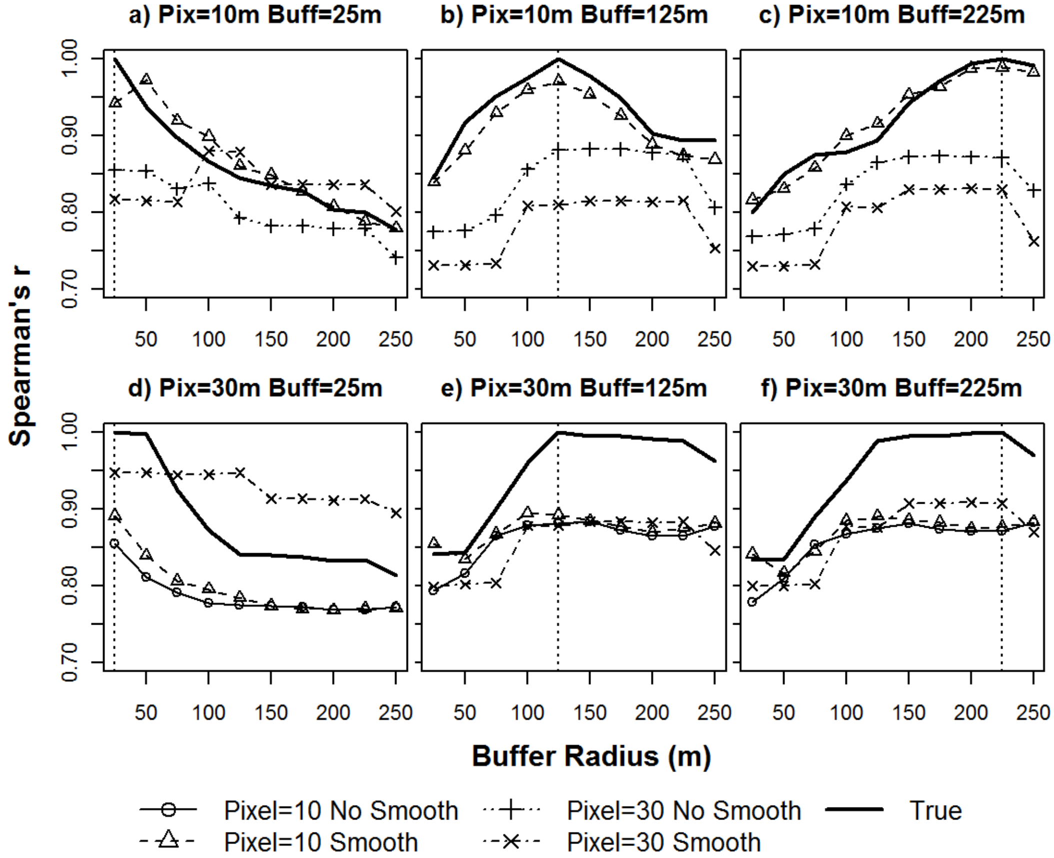
```
		for x = dd, N-dd, D do begin
			GRID(x,0) = f3(delta, GRID(x+dd,0), GRID(x-dd,0), GRID(x,dd),sigma,seed)
			GRID(x,N) = f3(delta, GRID(x+dd,N), GRID(x-dd,N), GRID(x,N-dd),sigma,seed)
			GRID(0,x) = f3(delta, GRID(0,x+dd), GRID(0,x-dd), GRID(dd,x),sigma,seed)
			GRID(N,x) = f3(delta, GRID(N,x+dd), GRID(N,x-dd), GRID(N-dd,x),sigma,seed)

			if wrap eq 1 then begin
				GRID(x,N) = GRID(x,0)
				GRID(N,x) = GRID(0,x)
			endif
		endfor

;#4 interpolate and offset interior grid points

for x = dd, N-dd, D do begin
		for y = D, N-dd, D do begin
			GRID(x,y) = f4 (delta, GRID(x,y+dd), GRID(x,y-dd), GRID(x+dd,y), GRID(x-
			dd,y),sigma,seed)
		endfor
endfor

;#5

for x =D, N-dd,D do begin
		for y= dd, N-dd, D do begin
			GRID(x,y)= f4(delta, GRID(x,y+dd), GRID(x,y-dd), GRID(x+dd,y), GRID(x-
			dd,y),sigma,seed)
		endfor
endfor

;#6 displace other points also if needed

if addition eq 1 then begin
		for x =0,N,D do begin
			for y = 0, N, D do begin
				GRID(x,y) = GRID(x,y) + delta * Gauss2(0.0,sigma,seed)
			endfor
```

```
    endfor

;#7

    for x = dd, N-dd, D do begin
        for y = dd,N-dd, D do begin
            GRID(x,y)= GRID (x,y) + delta * Gauss2(0.0,sigma,seed)
        endfor
    endfor
endif


D=D/2
dd= dd/2
endfor; ****loop 1

return, grid

End
```

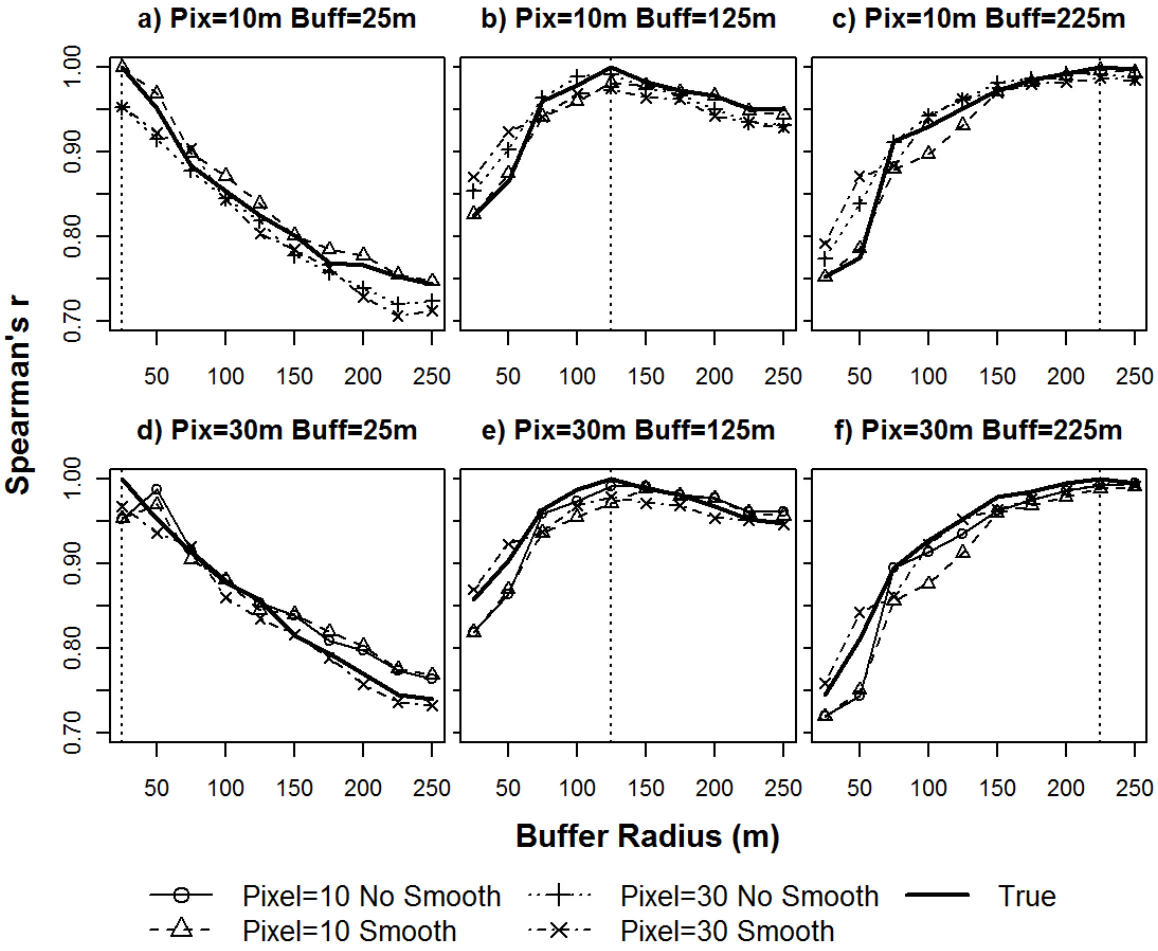
Appendix B



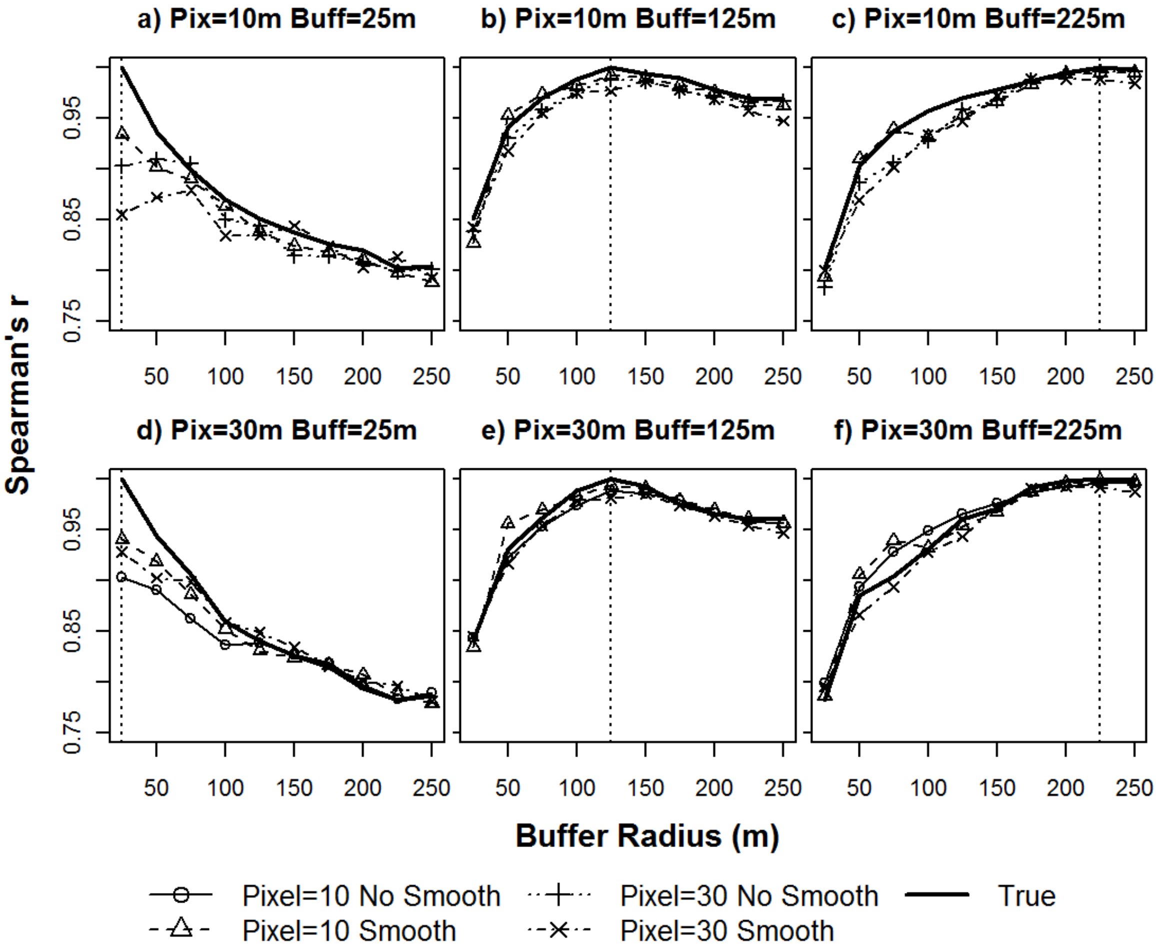
Graph of *r* values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for real landscape A. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.



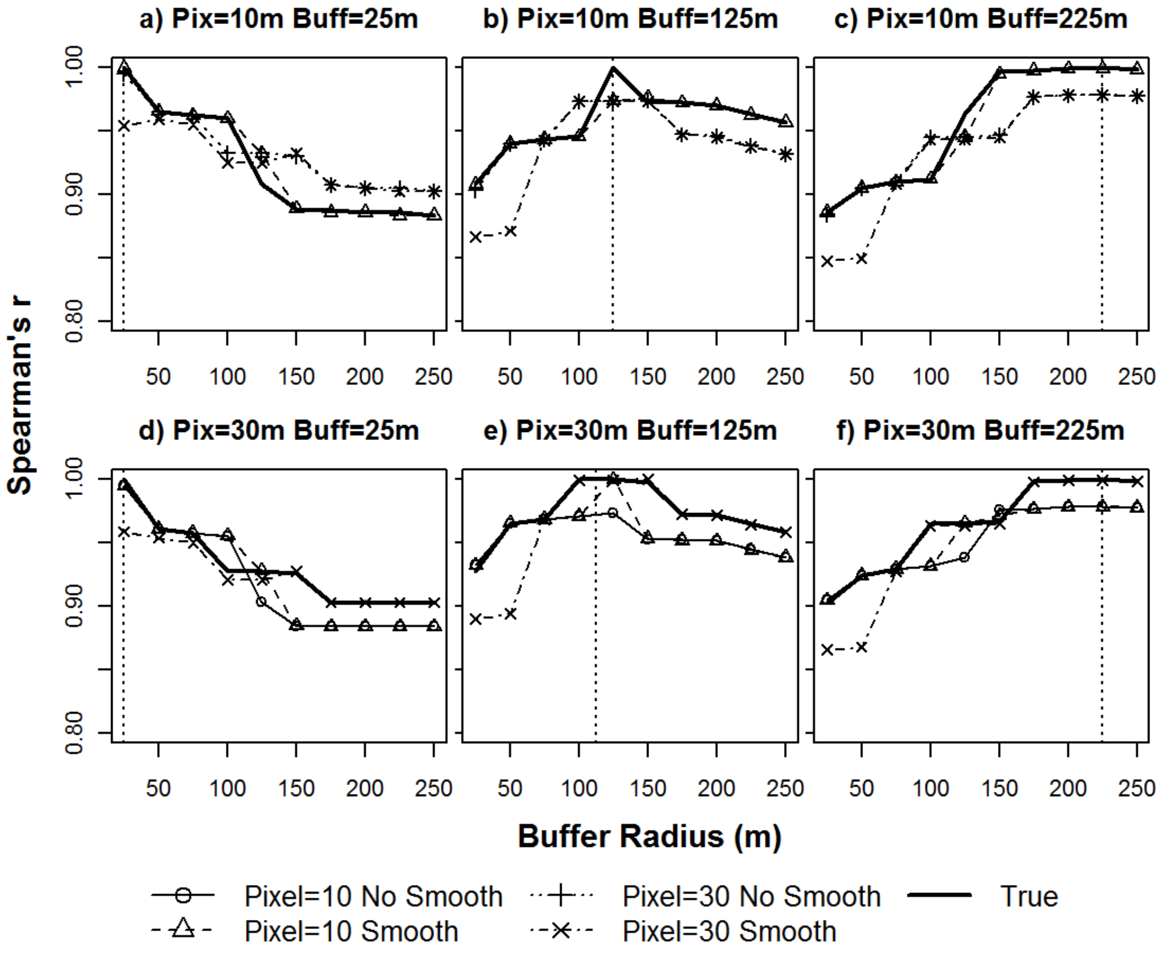
Graph of *r* values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for real landscape C. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.



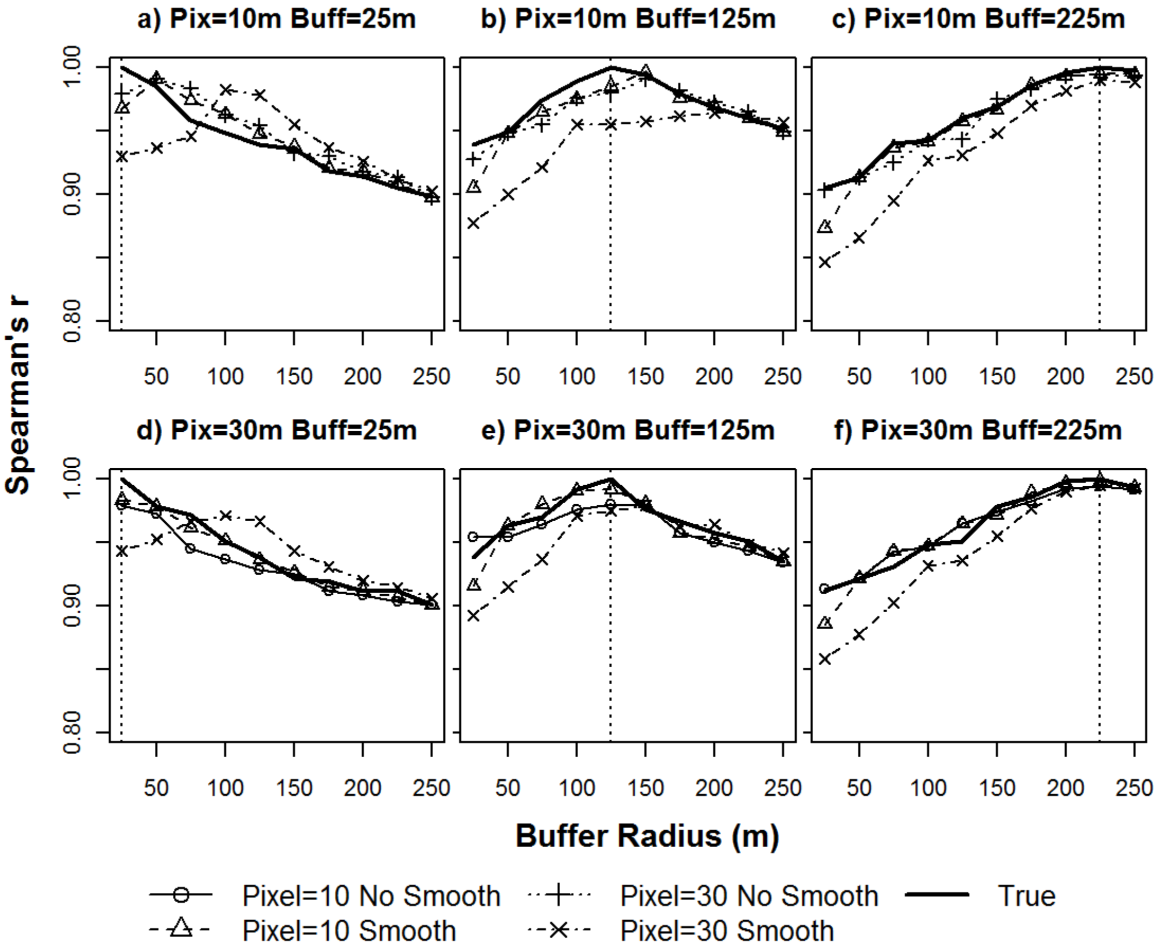
Graph of *r* values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for real landscape F. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.



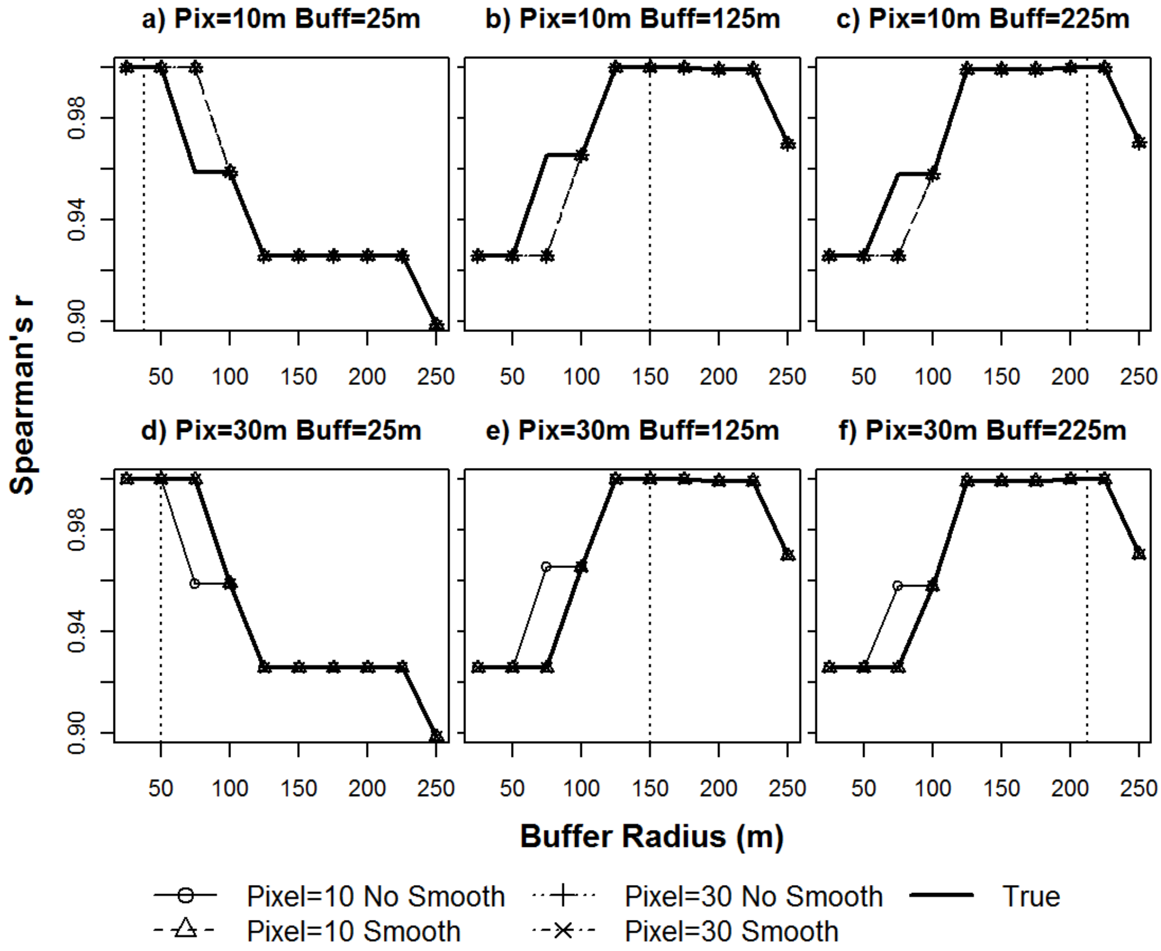
Graph of *r* values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for synthetic landscape H=0.1 P=0.5. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.



Graph of *r* values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for synthetic landscape H=0.5 P=0.25. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.



Graph of *r* values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for synthetic landscape H=0.5 P=0.5. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.



Graph of *r* values versus buffer radius for apparent and true landscapes and a range of derived ecological responses for synthetic landscape H=1 P=0.25. Curves in bold are based on the true landscape and buffer size used to derived the ecological response at a buffer radius and pixel size indicated above each plot. The other curves describe the *r* values versus buffer radius relationship derived with apparent landscapes. The buffer radius of the true ecological scale is indicated by the dotted vertical line.